

Building Fit-for-purpose Pharmacokinetic Models

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In Vitro to In Vivo
**Extrapolation for High
Throughput Prioritization
and Decision
Making Webinar Series**



Figure includes image from Thinkstock

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Introduction

- Toxicokinetics (TK) provide a bridge between hazard (e.g., what tissue concentration causes an effect?) and exposure (e.g., what dose do we get exposed to?)
- Traditional TK methods are resource intensive
- Relatively high throughput TK (HTTK) methods have been used by the pharmaceutical industry to prospectively evaluate success of planned clinical trials (Jamei, *et al.*, 2009; Wang, 2010)
 - A key application of HTTK has been “reverse dosimetry” (also called Reverse TK or RTK) (Tan et al., 2006)
 - RTK can approximately convert *in vitro* HTS results to daily doses needed to produce similar levels in a human for comparison to exposure data (Wetmore, *et al.*, 2012)
 - How accurate do predictions need to be?

Lex Parsimoniae

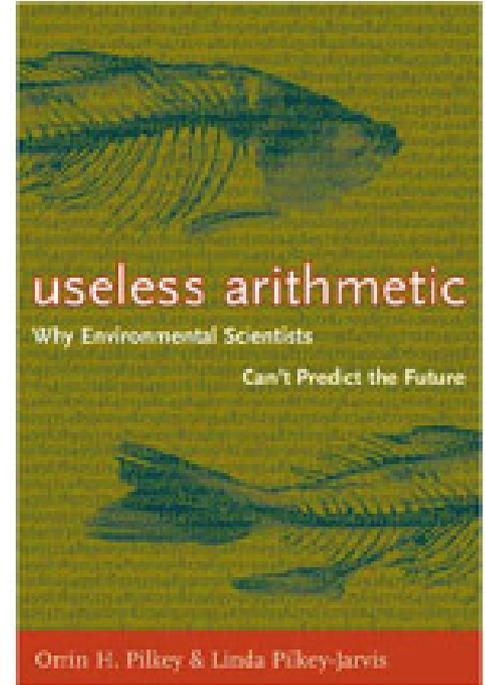
“Law of Parsimony”

“Among competing hypotheses, the one with the fewest assumptions should be selected.” William of Ockham

“...when you have eliminated the impossible, whatever remains, *however improbable*, must be the truth...”
Sherlock Holmes (Arthur Conan Doyle)

“PBPK? My immediate response: Junk in, junk out. The take-home is that most of the models [are] only as good as your understanding of the complexity of the system.”
Louis Guillette, Medical University of South Carolina

“As far as the laws of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality.” Albert Einstein



Orrin Pilkey &
Olinda Pilkey-Jarvis
(2007)

Accuracy vs. Precision

“Models can offer a means of avoiding the conclusions derived from actual experiments.” Kristin Shrader-Frechette, University of Notre Dame

“Essentially, all models are wrong, but some are useful.” George Box, University of Wisconsin

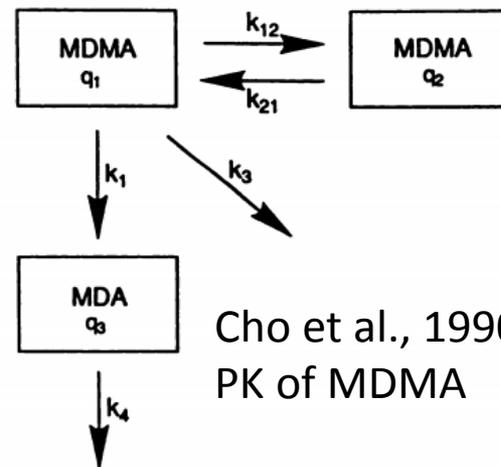
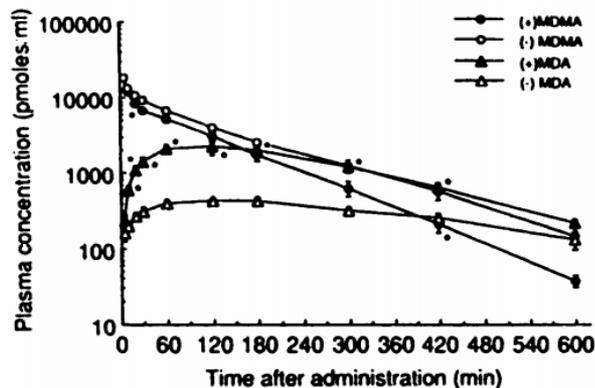
the signal and the noise and the noise and the noise and the noise why so many predictions fail— but some don't the noise and the noise nate silver noise and the noise

Nate Silver (2012)

1. Think probabilistically: Evaluate model performance systematically across as many chemicals (and chemistries) as possible
2. Forecasts change: Today's forecast reflects the best available data today but we must accept that new data and new models will cause predictions to be revised
3. Look for consensus: Evaluate as many models and predictors/predictions as possible

Complexity should fit the data..

“Since all models are wrong the scientist cannot obtain a ‘correct’ one by excessive elaboration. On the contrary[,] following William of Occam[, they] should seek an economical description of natural phenomena.” George Box, University of Wisconsin



Cho et al., 1990
PK of MDMA

Jones et al., 2012
PK of Statins

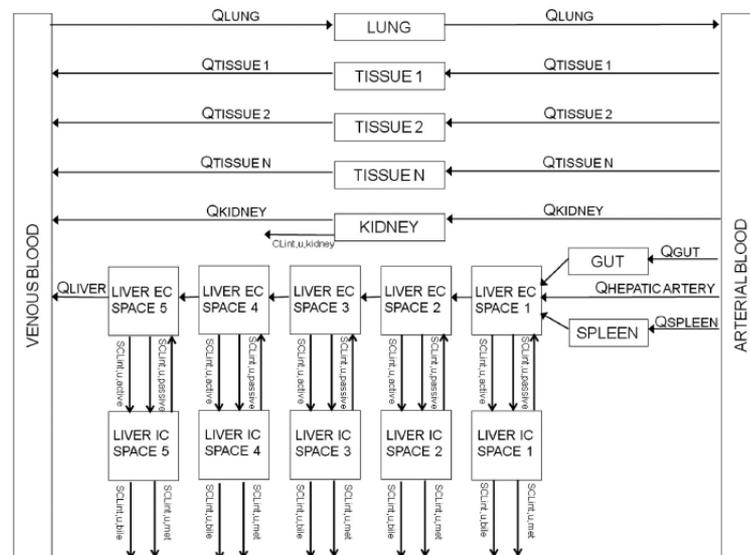
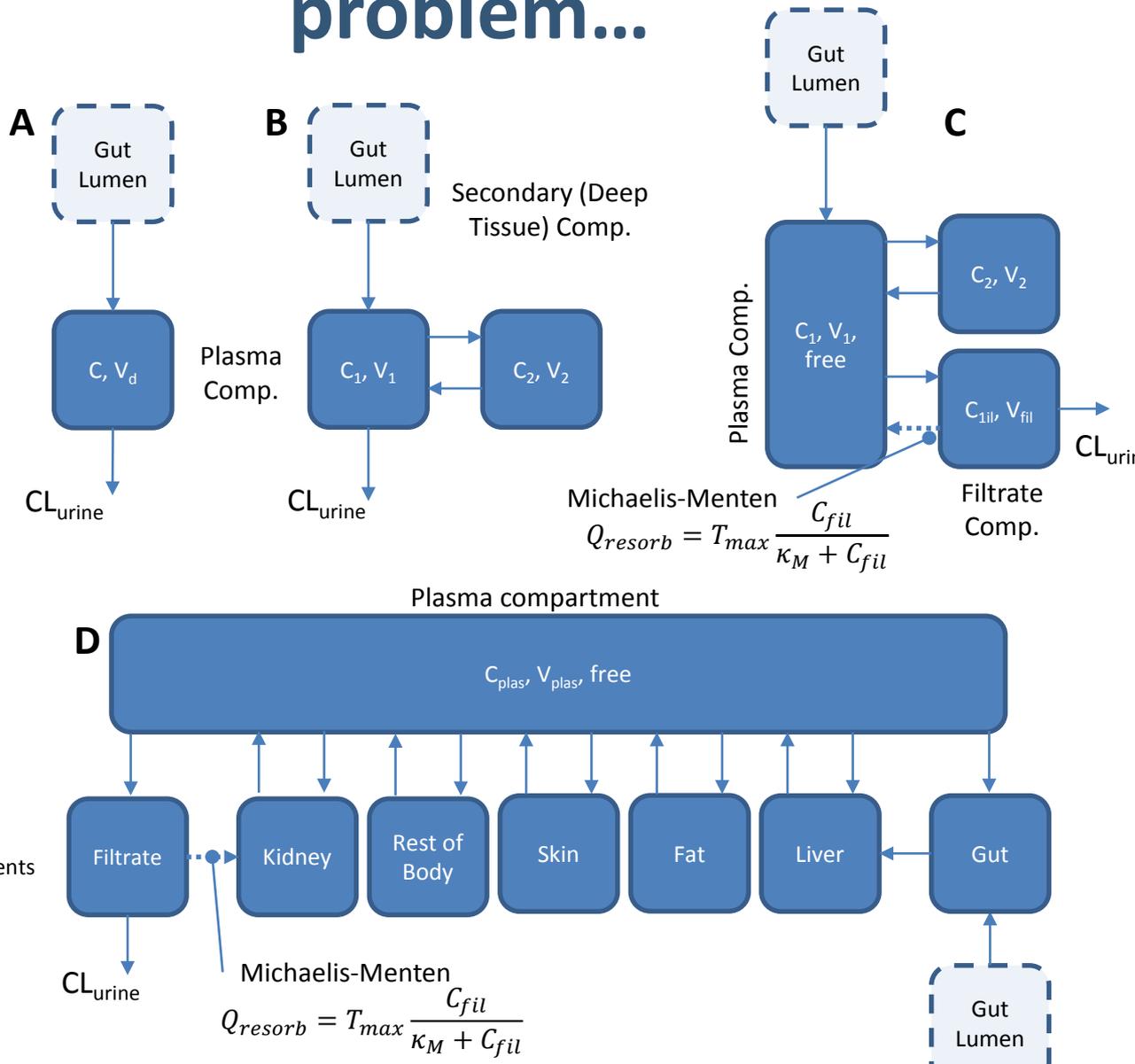


FIG. 2. Schematic diagram of the in vivo PBPK model. EC, extracellular; IC, intracellular.

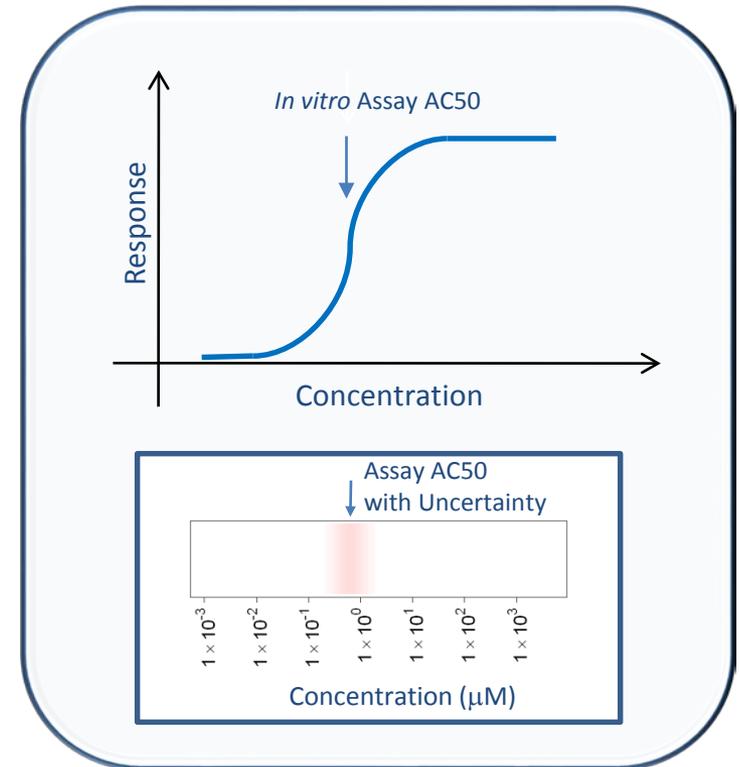
Complexity should fit the problem...

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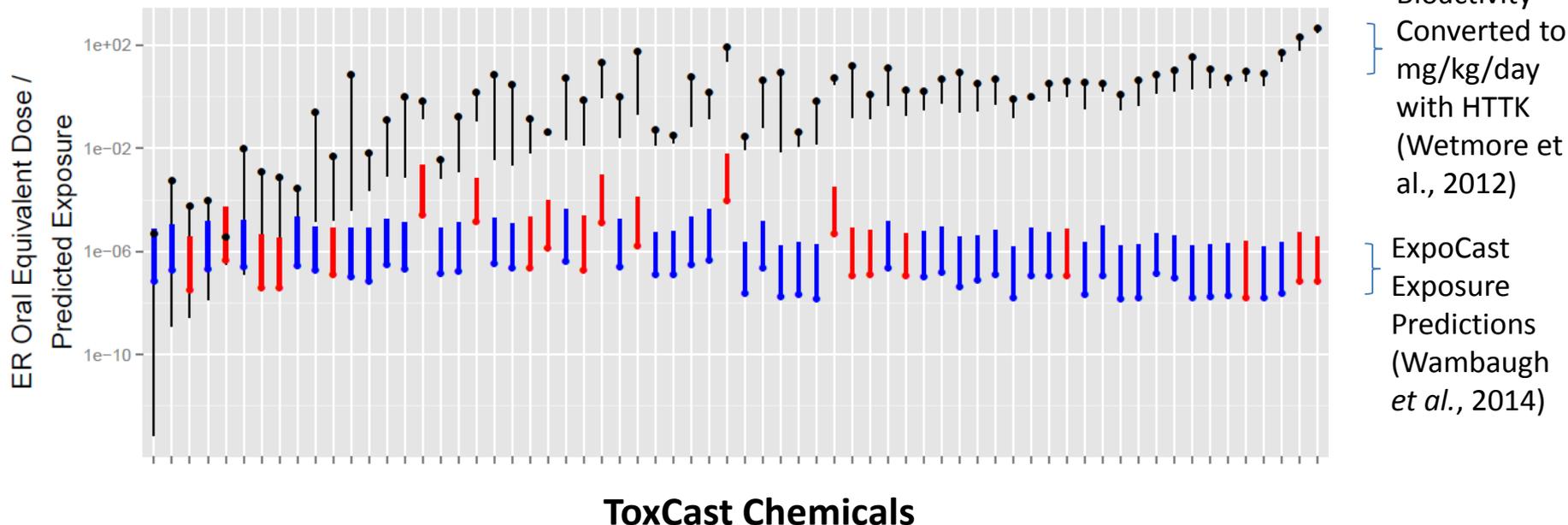
High-Throughput Bioactivity

- **Tox21:** Examining >10,000 chemicals using ~50 assays intended to identify interactions with biological pathways (Schmidt, 2009)
- **ToxCast:** For a subset (>1000) of Tox21 chemicals ran >800 additional assay endpoints (Judson et al., 2010)
- Most assays conducted in dose-response format (identify 50% activity concentration – AC50 – and efficacy if data described by a Hill function)
- All data is public:
<http://actor.epa.gov/dashboard2>



Pharmacokinetics Allows Context for High Throughput Screening

Endocrine disruption AOP (Judson et al., in prep.)

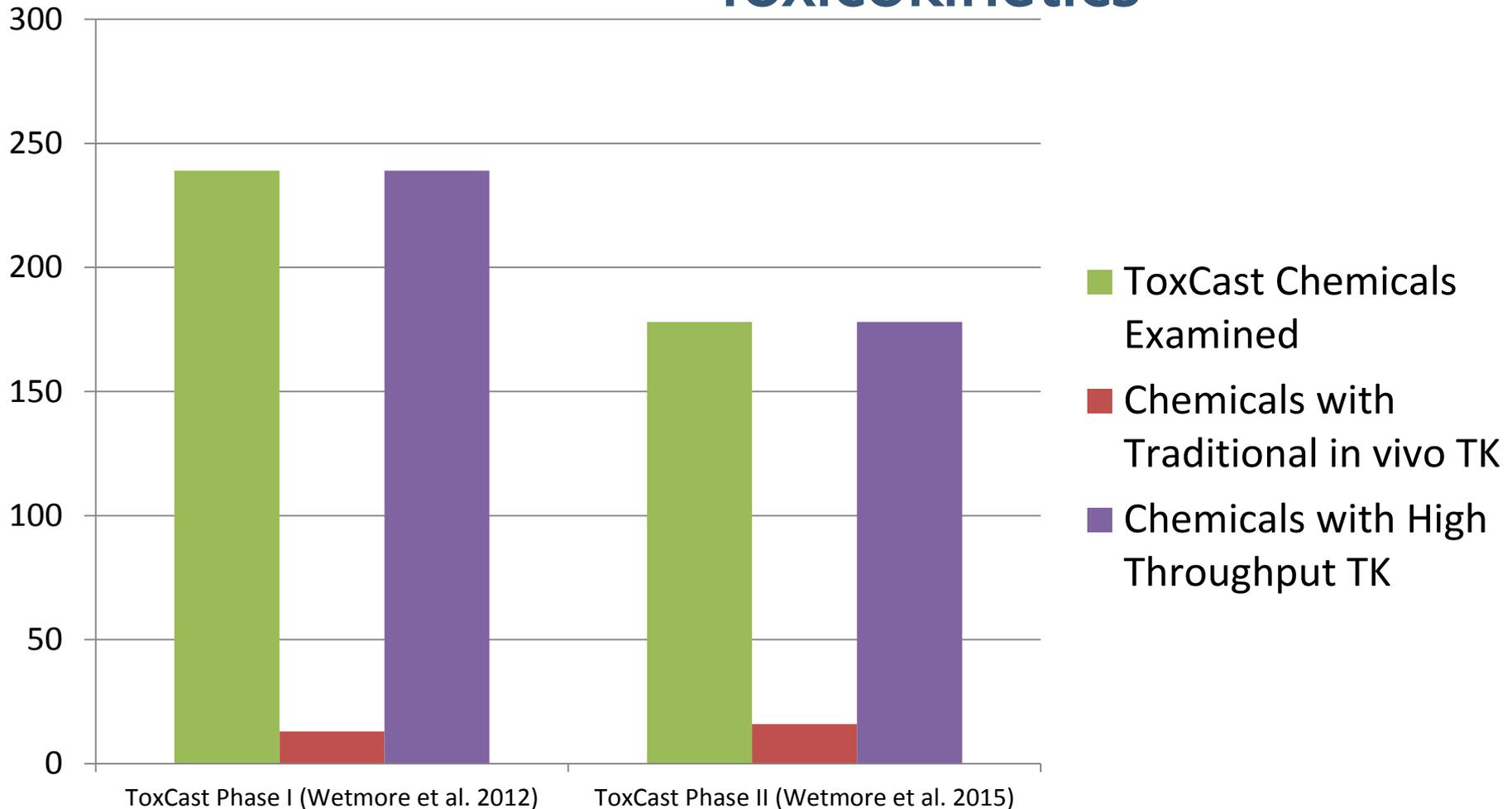


December, 2014 Panel:

“Scientific Issues Associated with Integrated Endocrine
Bioactivity and Exposure-Based Prioritization and Screening”

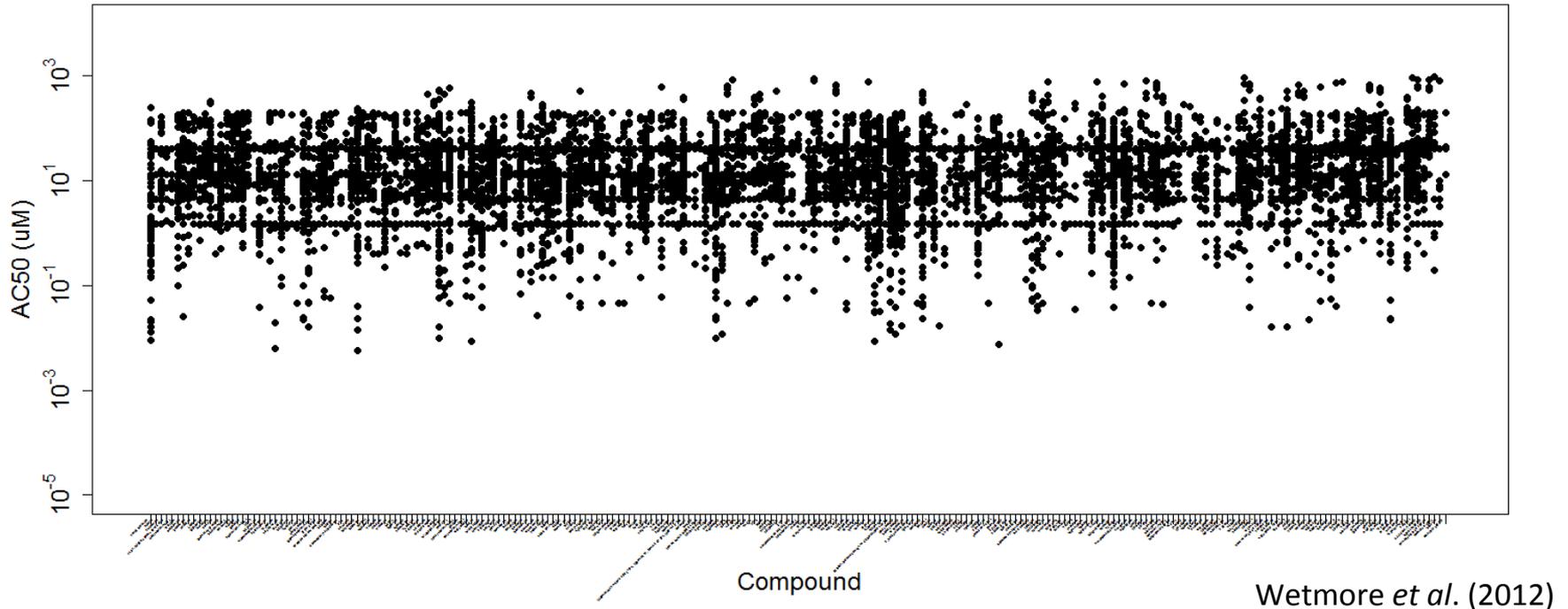
DOCKET NUMBER: EPA-HQ-OPP-2014-0614

The Need for *In Vitro* Toxicokinetics



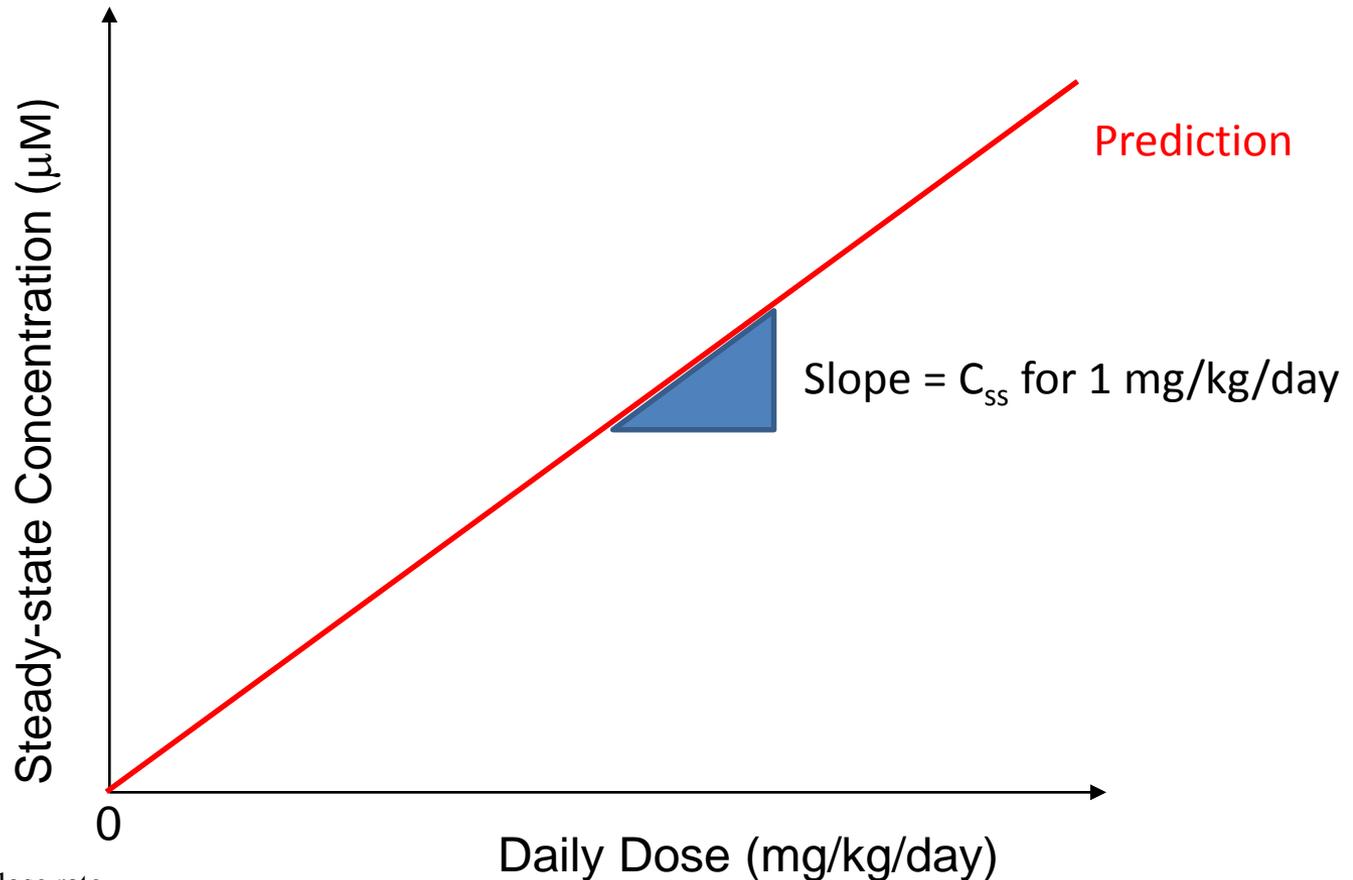
Studies like Wetmore et al. (2012), addressed the need for TK data using *in vitro* methods

ToxCast *in vitro* Bioactive Concentrations



- One point for each chemical-*in vitro* assay combination with a systematic (Hill function) concentration response curve
- How can we use toxicokinetics to convert these to human doses?

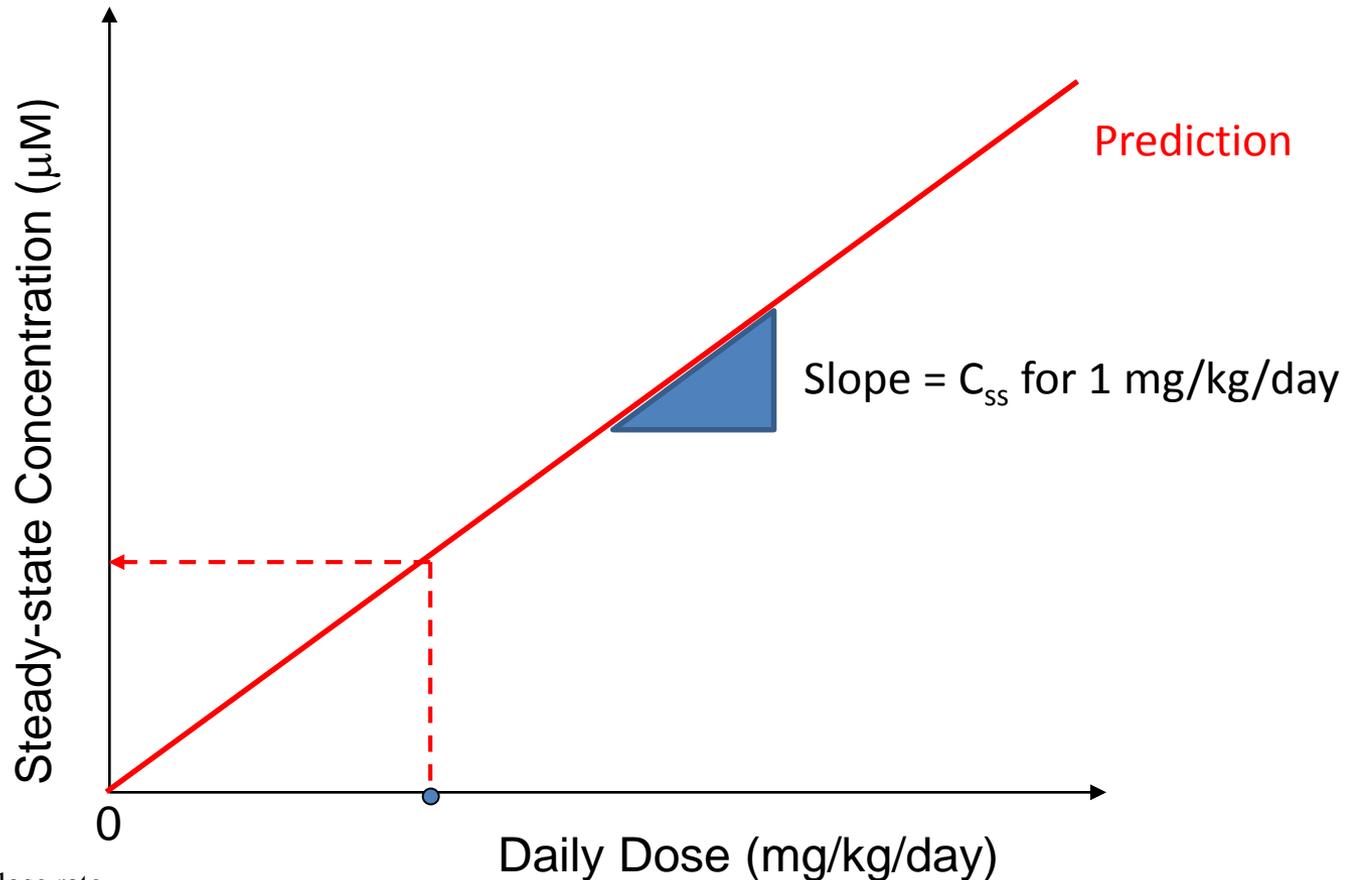
Steady-State is Linear with Dose



$$C_{ss} = \frac{\text{oral dose rate}}{\left(\text{GFR} * F_{ub} \right) + \left(Q_l * F_{ub} * \frac{Cl_{int}}{Q_l + F_{ub} * Cl_{int}} \right)}$$

- Can calculate predicted steady-state concentration (C_{ss}) for a 1 mg/kg/day dose and multiply to get concentrations for other doses

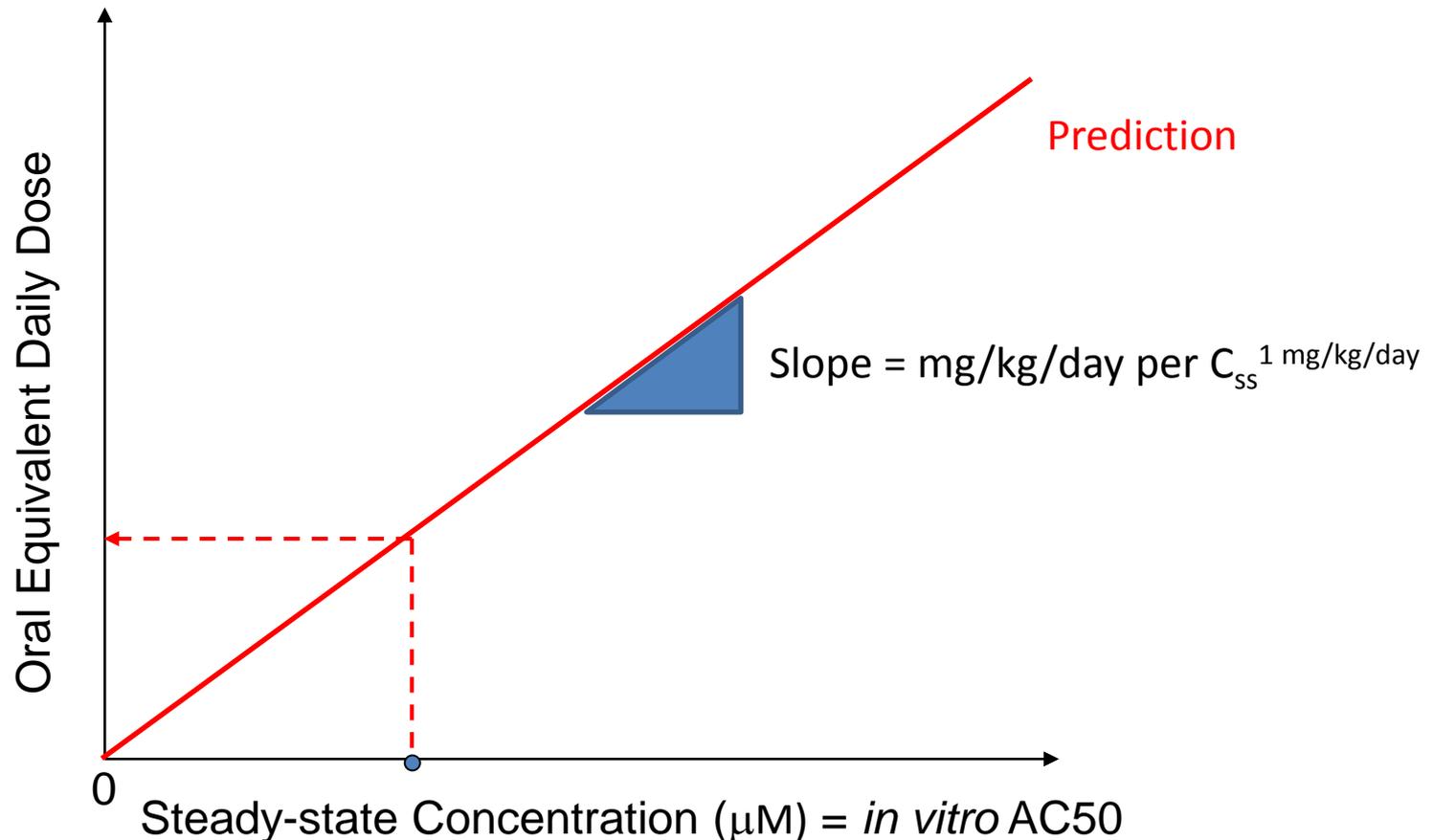
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$$C_{ss} = \frac{\text{oral dose rate}}{\left(\text{GFR} * F_{ub} \right) + \left(Q_l * F_{ub} * \frac{Cl_{int}}{Q_l + F_{ub} * Cl_{int}} \right)}$$

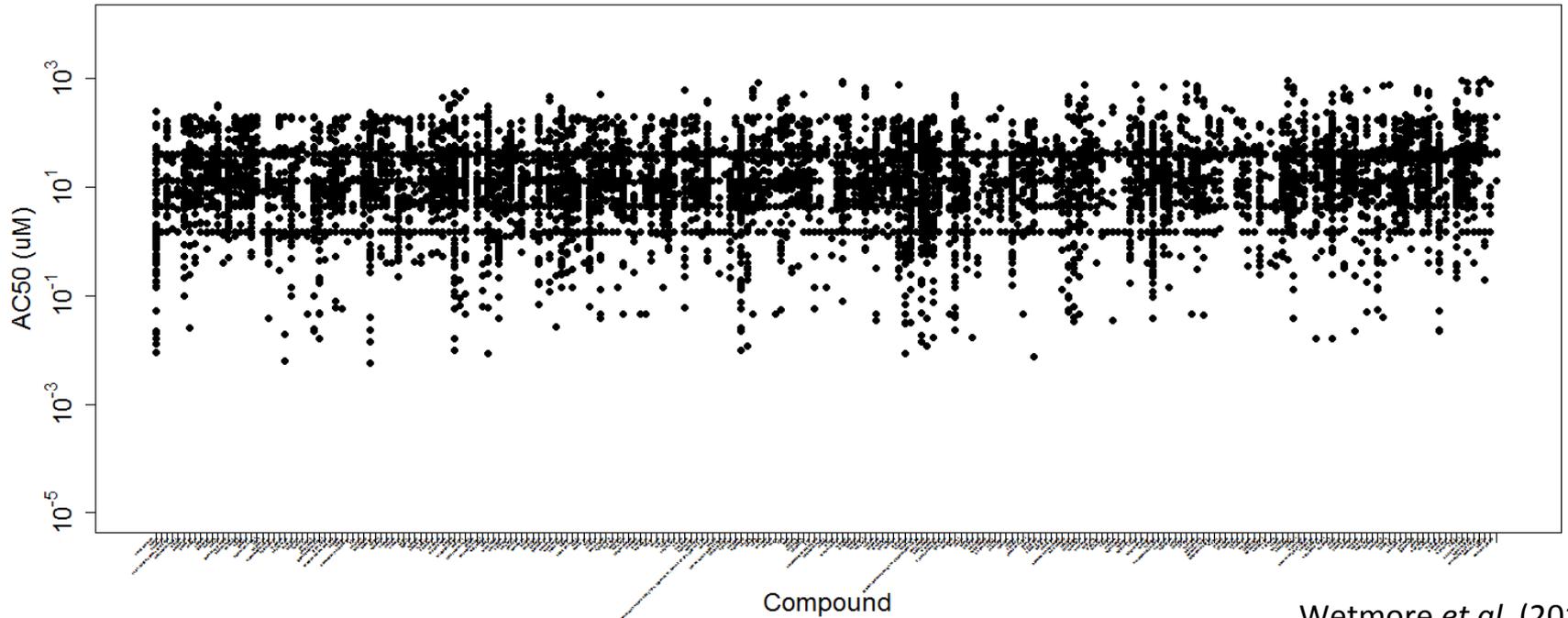
- Can calculate predicted steady-state concentration (C_{ss}) for a 1 $\text{mg}/\text{kg}/\text{day}$ dose and multiply to get concentrations for other doses

HTTK Allows Steady-State *In Vitro*- *In Vivo* Extrapolation (IVIVE)



- Swap the axes (this is the “reverse” part of reverse dosimetry)
- Can divide bioactive concentration by C_{ss} for for a 1 mg/kg/day dose to get oral equivalent dose

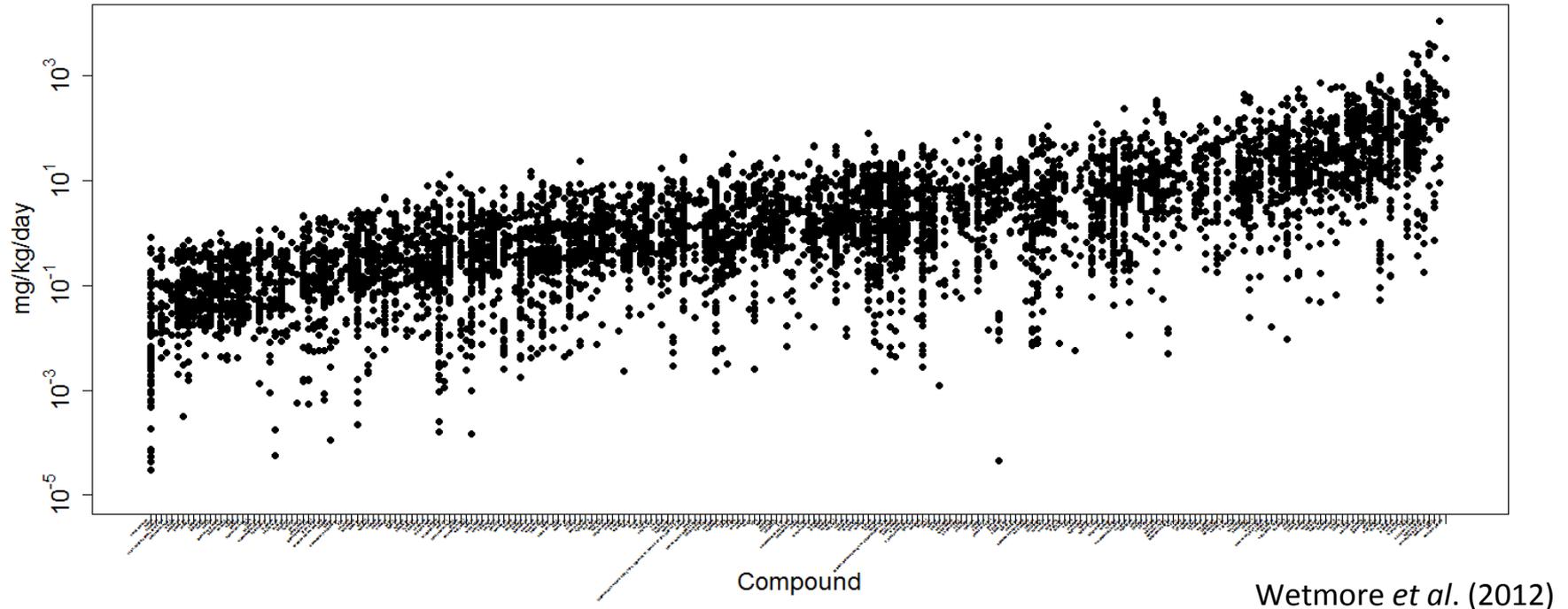
ToxCast *in vitro* Bioactive Concentrations



Wetmore *et al.* (2012)

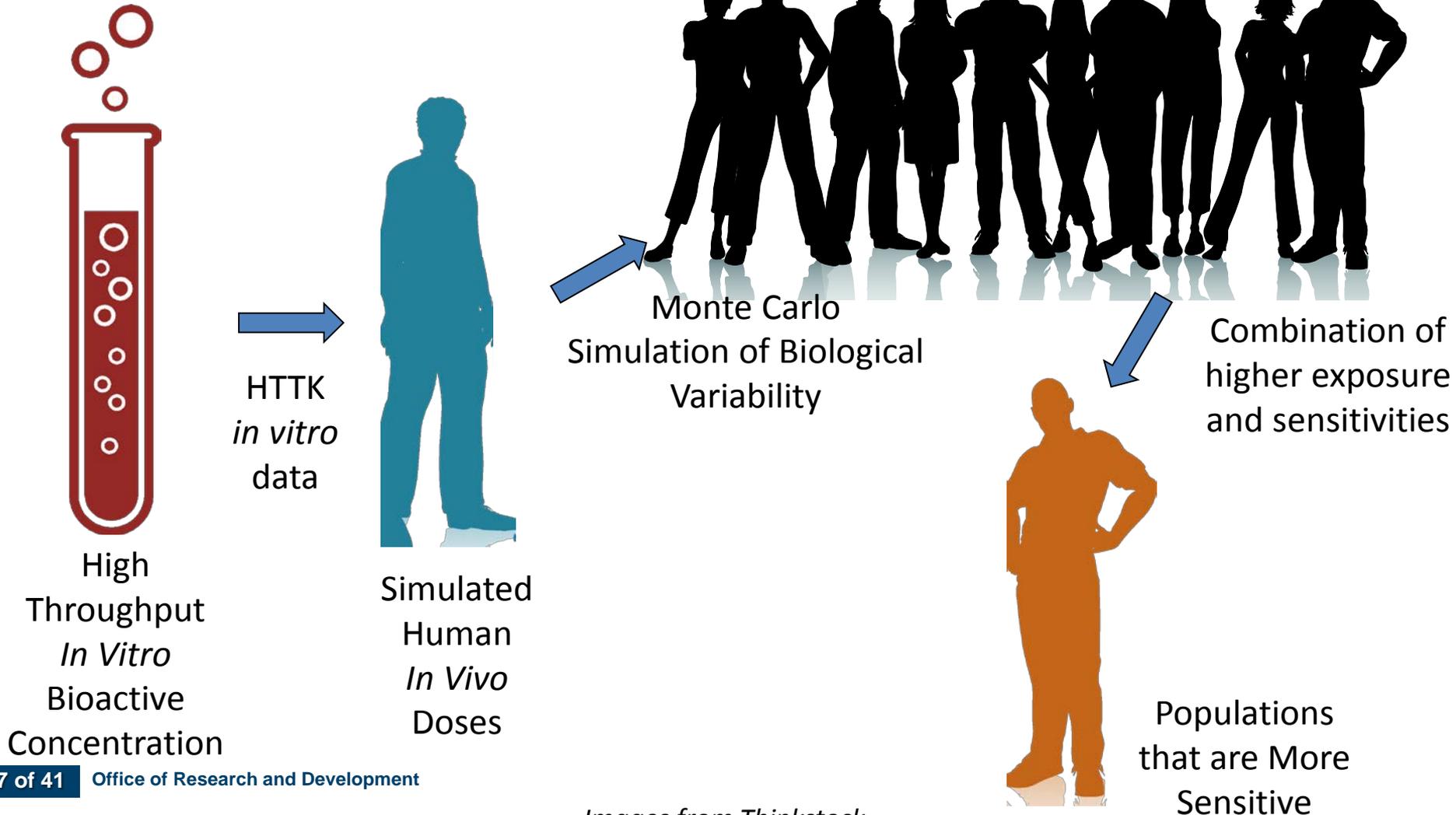
- It appears harder to prioritize on bioactive *in vitro* concentration without *in vivo* context

HTTK Oral Equivalents



- Translation from *in vitro* to steady-state oral equivalent doses allow greater discrimination between effective chemical potencies

Reverse Dosimetry with HTTK

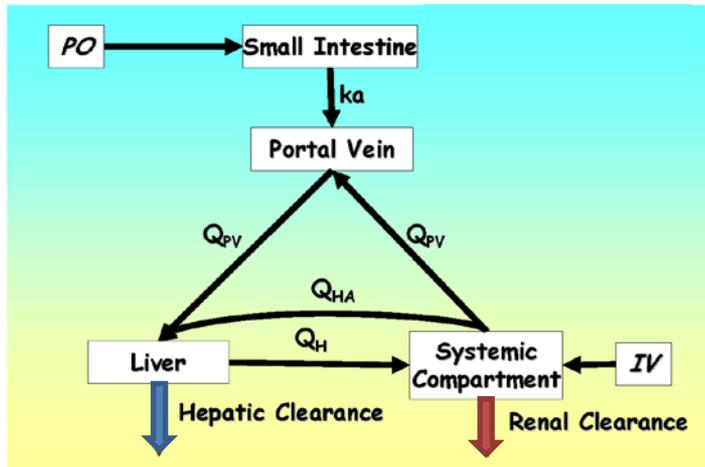


Images from Thinkstock

Variability in this Steady-State TK Model

Jamei *et al.* (2009)

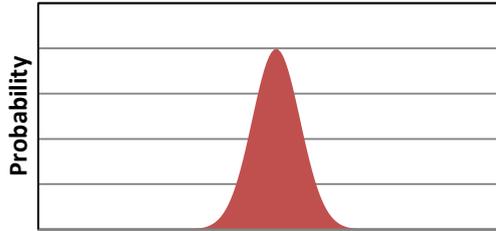
Minimal Model: Lumped Single Distribution Volume



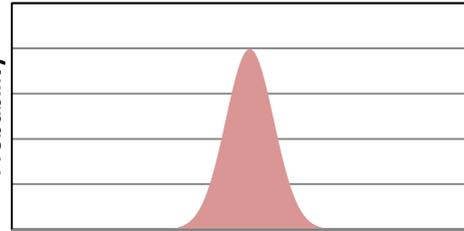
$$C_{ss} = \frac{\text{oral dose rate}}{\underbrace{(GFR * F_{ub})}_{\text{(Passive) Renal Clearance}} + \underbrace{\left(Q_l * F_{ub} * \frac{Cl_{int}}{Q_l + F_{ub} * Cl_{int}} \right)}_{\text{Hepatic Clearance (Metabolism)}}$$

- *In vitro* clearance ($\mu\text{L}/\text{min}/10^6$ hepatocytes) is scaled to a whole organ clearance using the density of hepatocytes per gram of liver and the volume of the liver (which varies between individuals)
- Glomerular filtration rate (GFR) and blood flow to the liver (Q_l) both vary from individual to individual
- Further assume that measured HTK parameters have 30% coefficient of variation

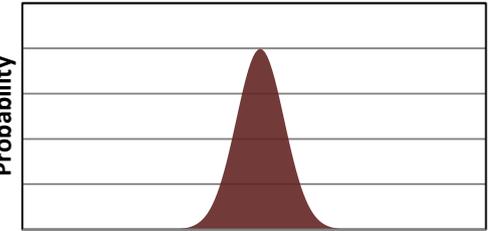
Monte Carlo (MC) Approach to Variability: SimCYP (Pharma) Approach



log Liver Flow (Q_l)

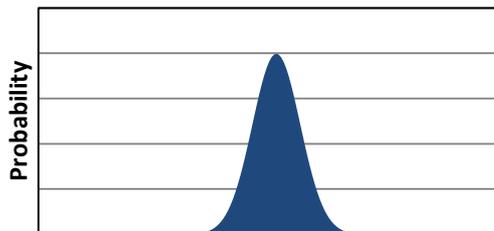
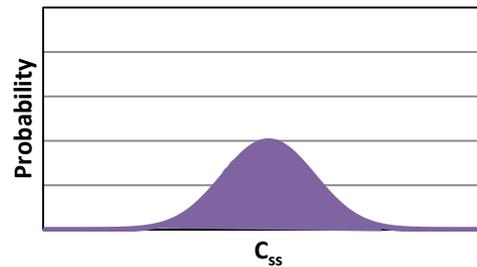


log Glomerular Filtration Rate (GFR)

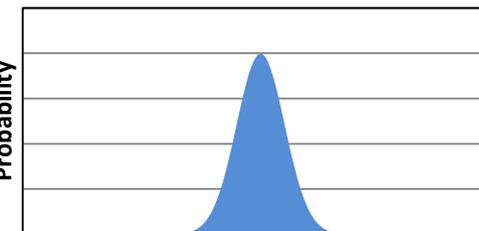


log Liver Volume

$$C_{ss} = \frac{\text{oral dose rate}}{(GFR * F_{ub}) + \left(Q_l * F_{ub} * \frac{Cl_{int}}{Q_l + F_{ub} * Cl_{int}} \right)}$$



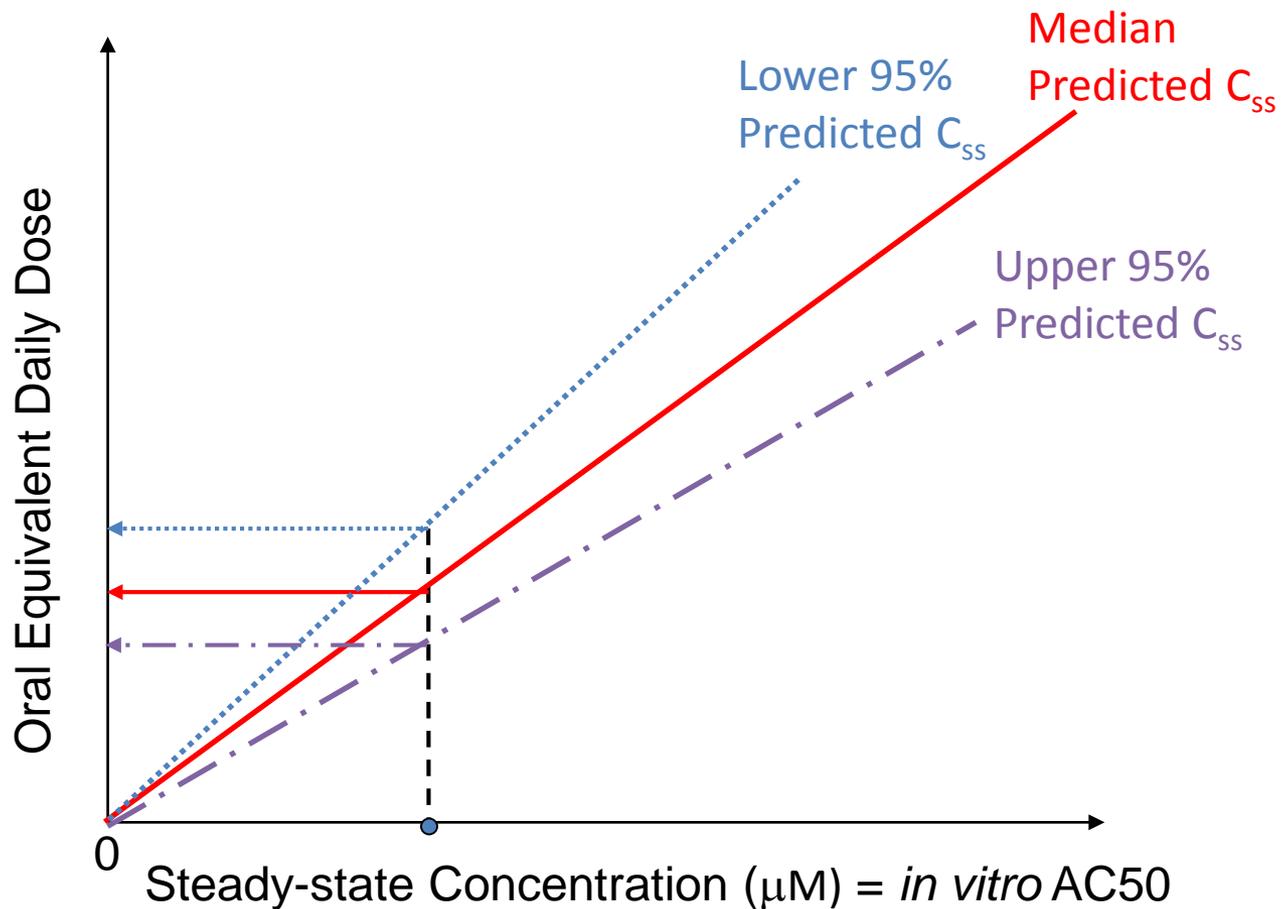
log $Cl_{int}^{in\ vitro}$



log f_{ub}



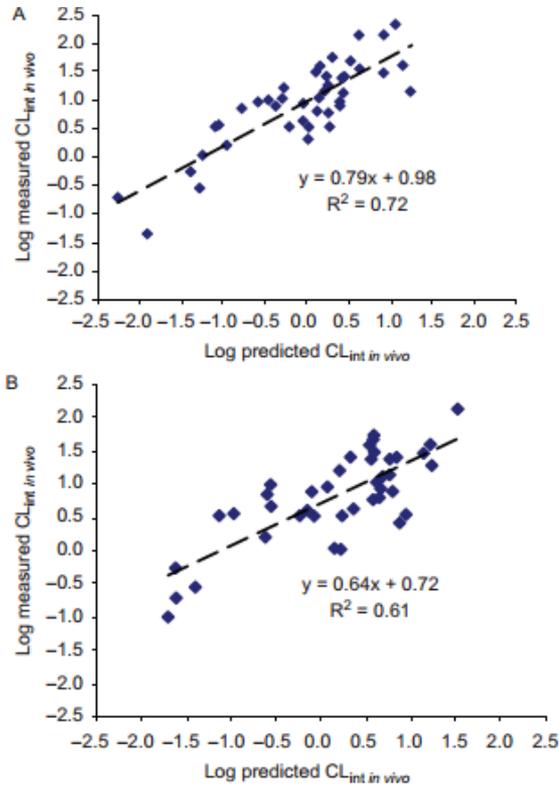
Steady-State In Vitro-In Vivo Extrapolation (IVIVE)



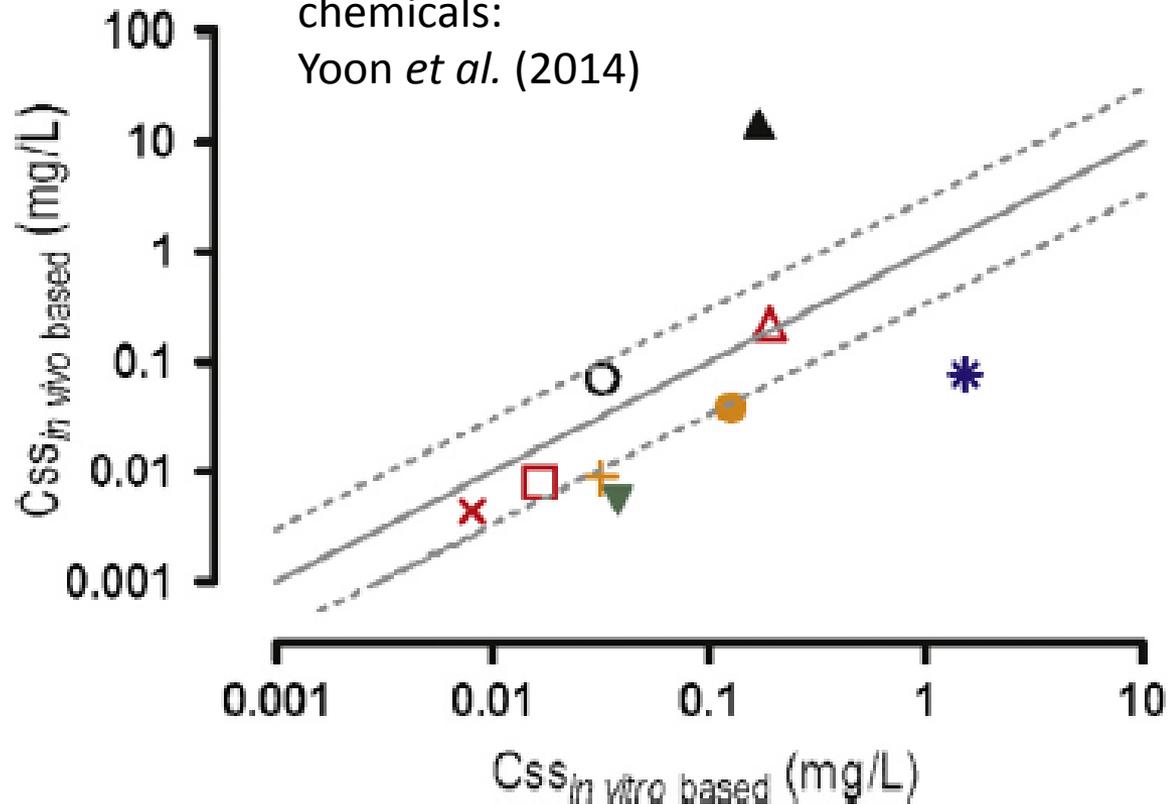
- The higher the predicted C_{ss} , the lower the oral equivalent dose, so the upper 95% predicted C_{ss} from the MC has a lower oral equivalent dose

Characterizing Accuracy of HTTK

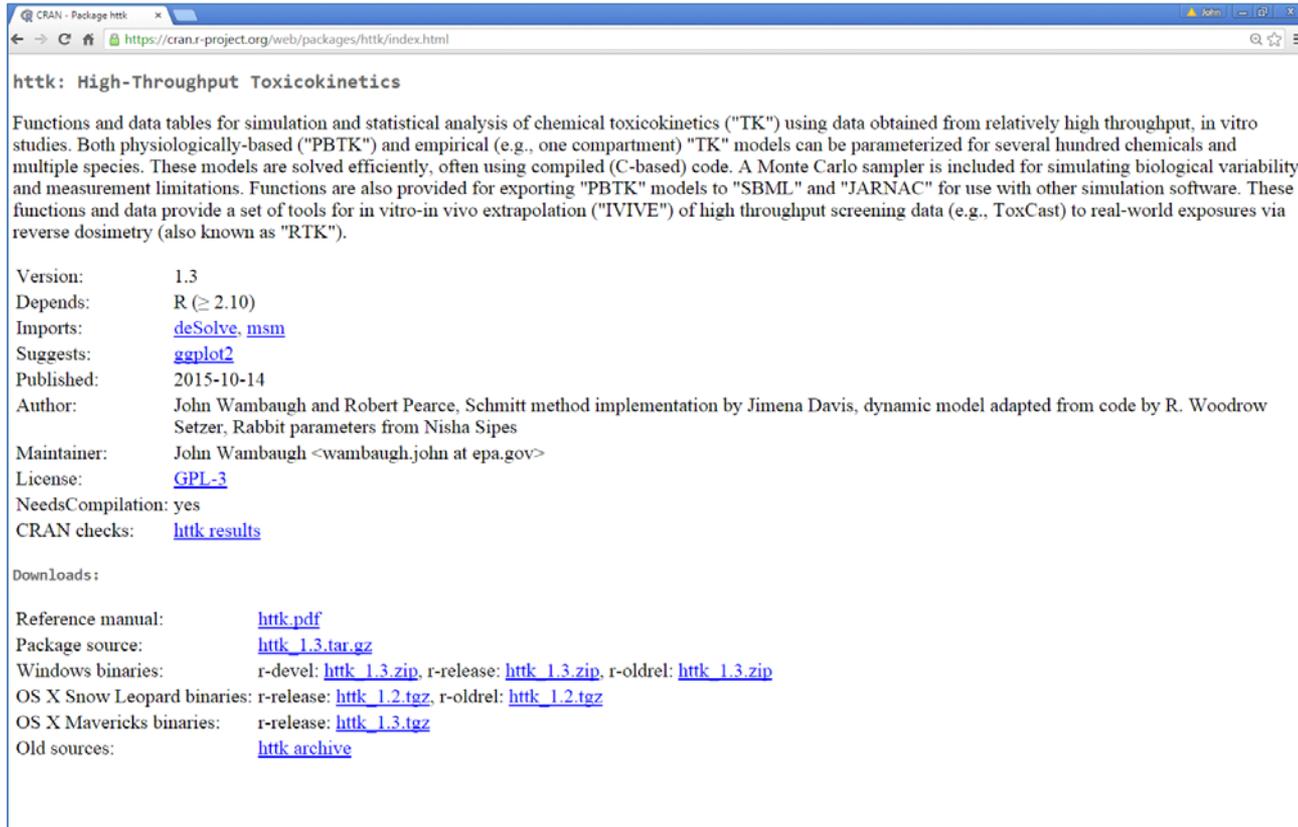
Wang (2010): *In vitro* predictions typically within a factor of three for pharmaceuticals



Environmental
chemicals:
Yoon *et al.* (2014)



543 Chemicals with httk R Package



The screenshot shows the CRAN website for the httk R package. The page title is "httkt: High-Throughput Toxicokinetics". The description states: "Functions and data tables for simulation and statistical analysis of chemical toxicokinetics ('TK') using data obtained from relatively high throughput, in vitro studies. Both physiologically-based ('PBTK') and empirical (e.g., one compartment) 'TK' models can be parameterized for several hundred chemicals and multiple species. These models are solved efficiently, often using compiled (C-based) code. A Monte Carlo sampler is included for simulating biological variability and measurement limitations. Functions are also provided for exporting 'PBTK' models to 'SBML' and 'JARNAC' for use with other simulation software. These functions and data provide a set of tools for in vitro-in vivo extrapolation ('IVIVE') of high throughput screening data (e.g., ToxCast) to real-world exposures via reverse dosimetry (also known as 'RTK')."

Version: 1.3
Depends: R (\geq 2.10)
Imports: [deSolve](#), [msm](#)
Suggests: [ggplot2](#)
Published: 2015-10-14
Author: John Wambaugh and Robert Pearce, Schmitt method implementation by Jimena Davis, dynamic model adapted from code by R. Woodrow Setzer, Rabbit parameters from Nisha Sipes
Maintainer: John Wambaugh <wambaugh.john@epa.gov>
License: [GPL-3](#)
NeedsCompilation: yes
CRAN checks: [httkt results](#)

Downloads:

Reference manual: [httkt.pdf](#)
Package source: [httkt_1.3.tar.gz](#)
Windows binaries: r-devel: [httkt_1.3.zip](#), r-release: [httkt_1.3.zip](#), r-oldrel: [httkt_1.3.zip](#)
OS X Snow Leopard binaries: r-release: [httkt_1.2.tgz](#), r-oldrel: [httkt_1.2.tgz](#)
OS X Mavericks binaries: r-release: [httkt_1.3.tgz](#)
Old sources: [httkt archive](#)

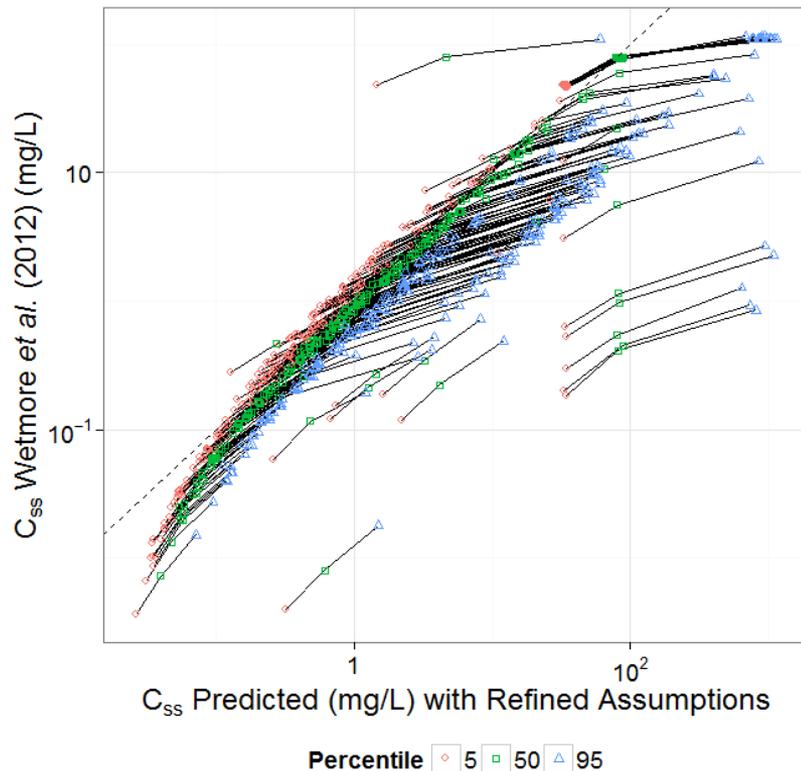
<https://cran.r-project.org/web/packages/httkt/>

Can access this from the R GUI: "Packages" then "Install Packages"

443 with PBTK models

Lead developer Robert Peace

Comparison Between httk and SimCYP



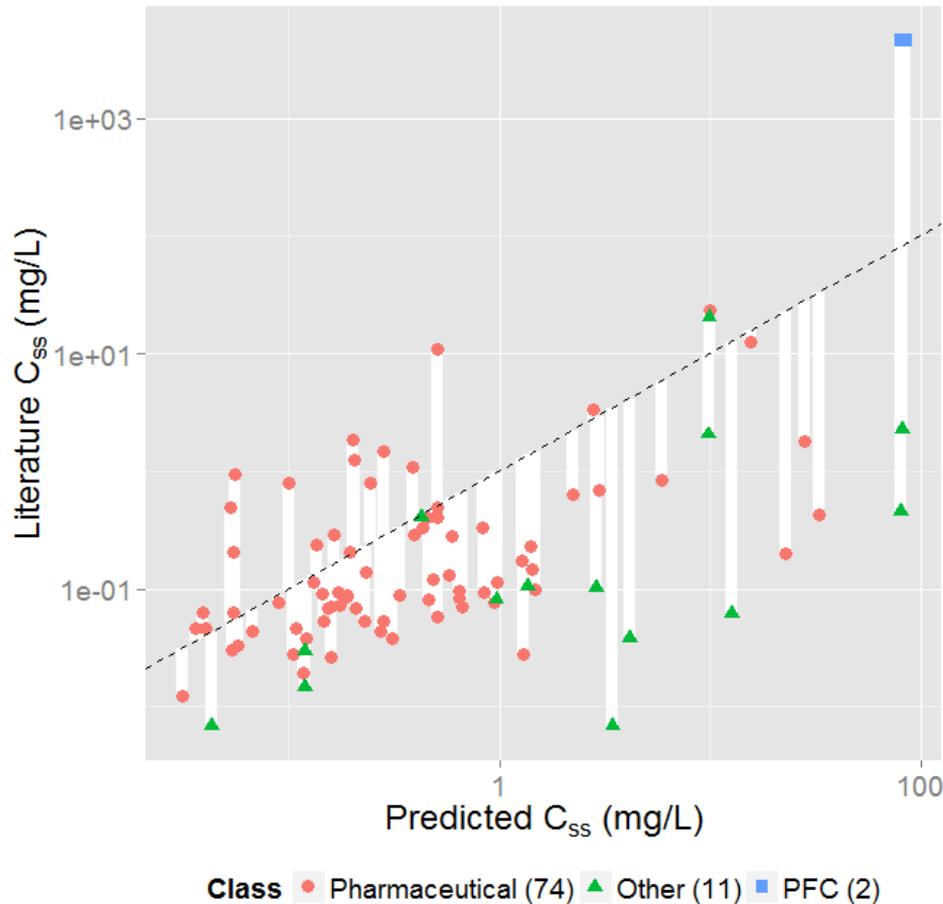
- In the Rotroff et al. (2010) and Wetmore et al. (2012, 2013, 2014, 2015) papers SimCYP was used to predict distributions of C_{ss} from *in vitro* data

- We can reproduce the results from those publications for most chemicals using our implementation of Monte Carlo.

- Any one chemical's median and quantiles are connected by a dotted line.

The RED assay for measuring protein binding fails in some cases because the amount of free chemical is below the limit of detection. For those chemicals a default value of 0.5% free was used. We have replaced the default value with random draws from a uniform distribution from 0 to 1%.

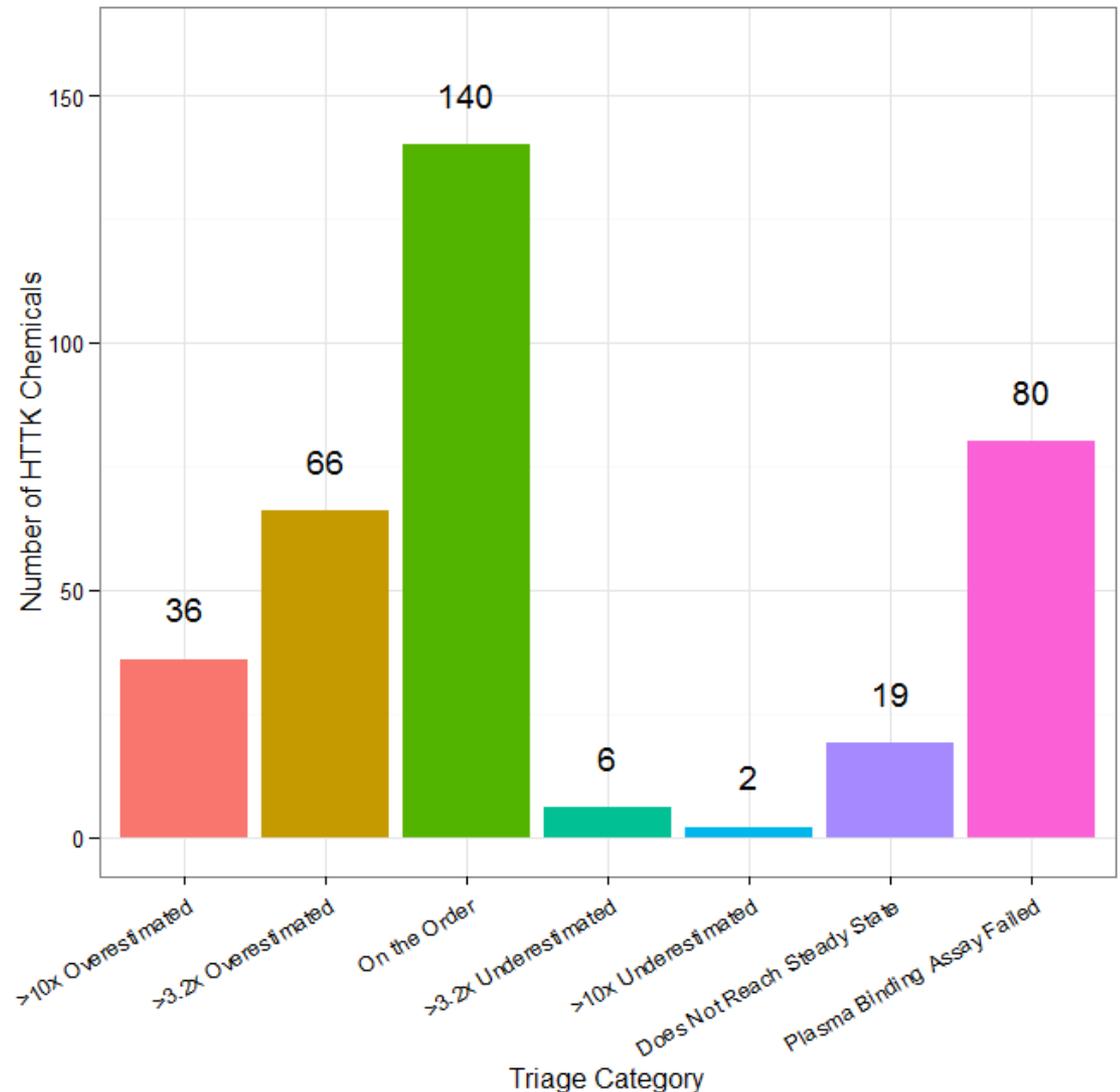
Using *in vivo* Data to Evaluate RTK



- When we compare the C_{ss} predicted from *in vitro* HTKK with *in vivo* C_{ss} values determined from the literature we find limited correlation ($R^2 \sim 0.34$)
- The dashed line indicates the identity (perfect predictor) line:
 - Over-predict for 65
 - Under-predict for 22
- The white lines indicate the discrepancy between measured and predicted values (the residual)

Toxicokinetic Triage

- Through comparison to *in vivo* data, a cross-validated (random forest) predictor of success or failure of HHTK has been constructed
- Add categories for chemicals that do not reach steady-state or for which plasma binding assay fails
- All chemicals can be placed into one of seven confidence categories

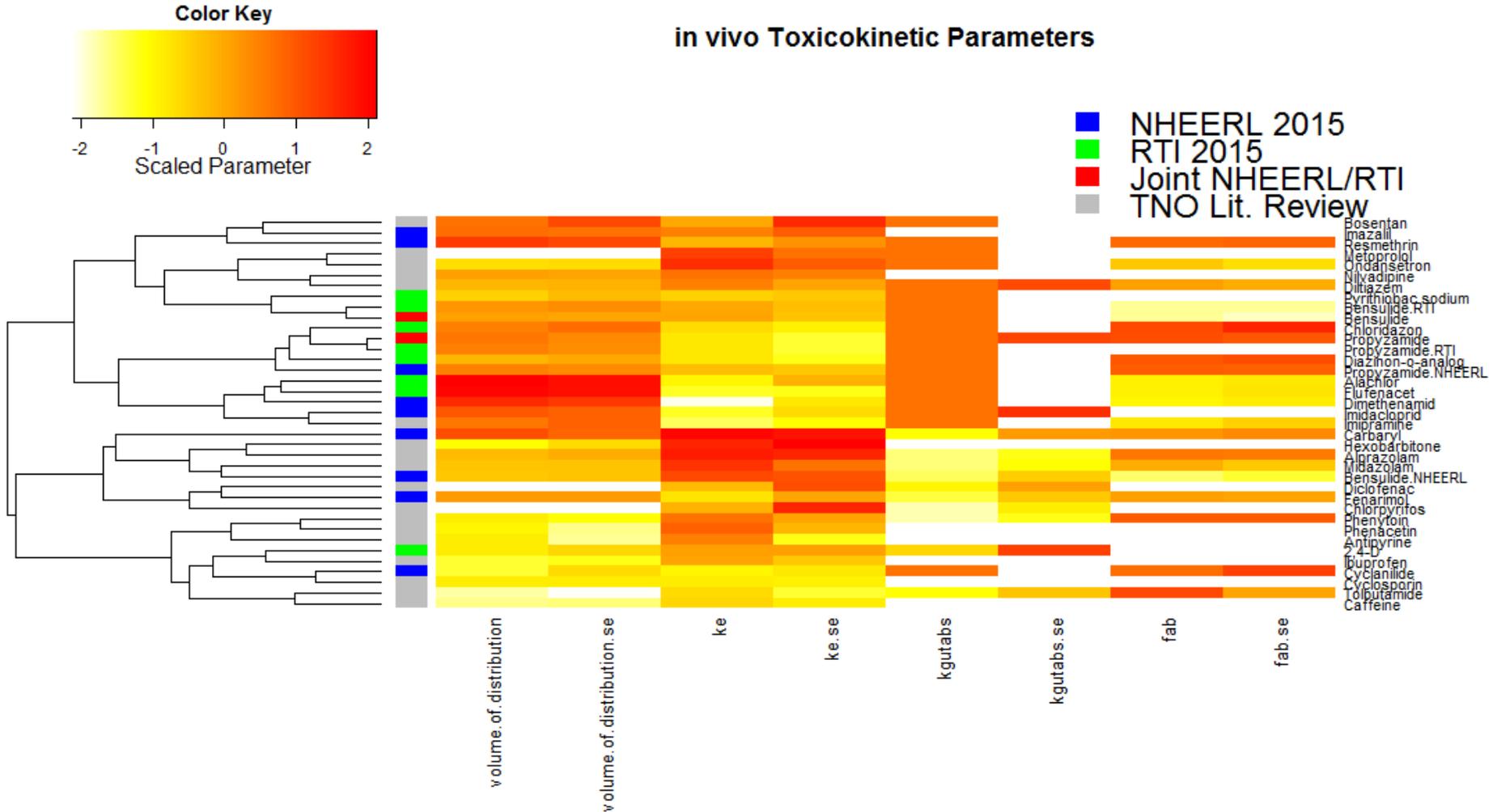


New *In Vivo* PK Data Set

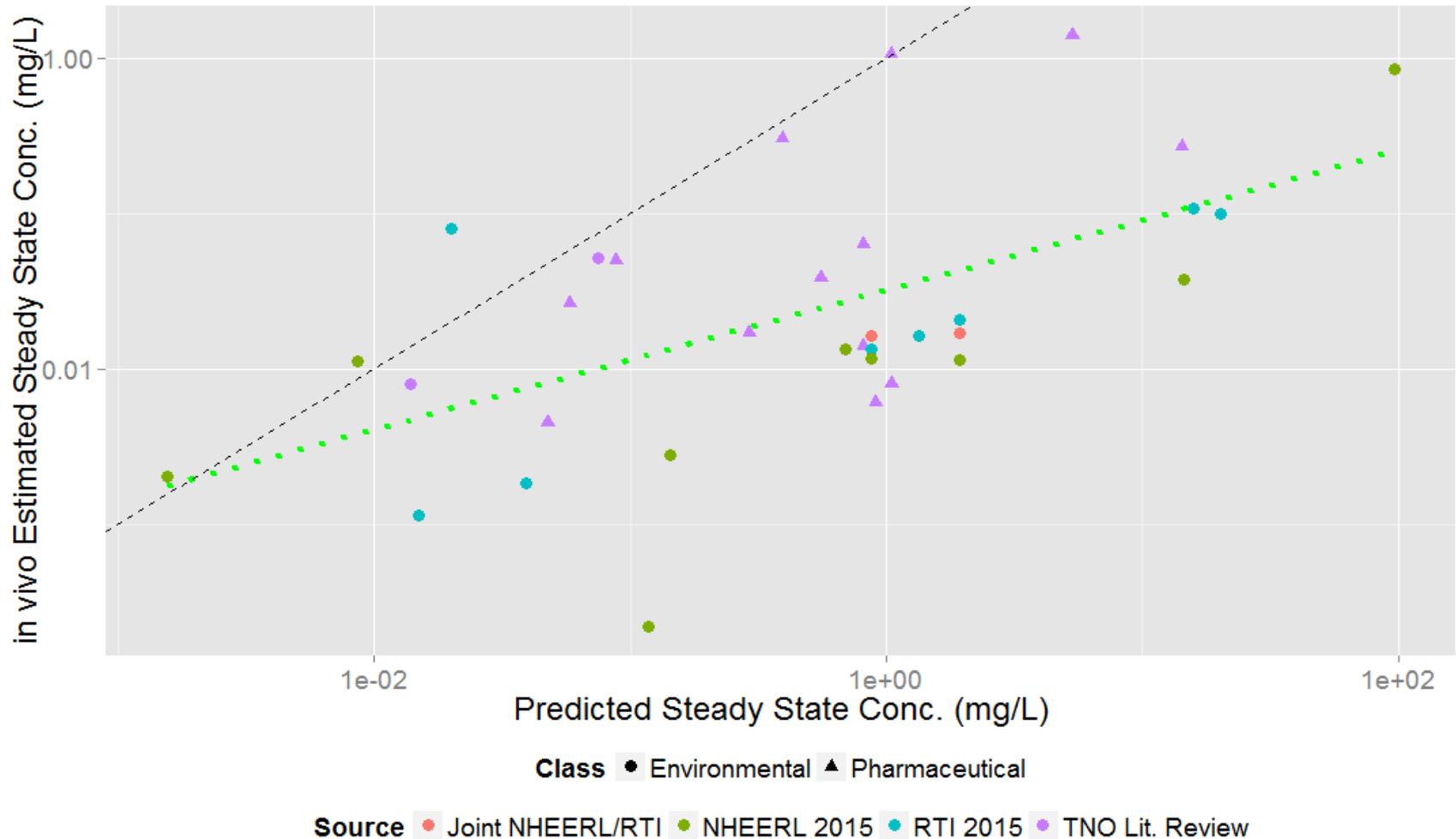
- Could the difference be related to inhomogeneous C_{ss} data?
 - Initially relying on Obach (2008) data plus data curated by TNO (Sieto Bosgra lead) from literature
- Only 13 non-pharmaceuticals examined so far
- Cross lab study:
 - 20 chemicals examined by NHEERL (Mike Hughes lead)
 - 8 chemicals examined by RTI (Tim Fennell lead)
 - 2 overlap chemicals (Bensulide and Propyzamide)

An *In Vivo* Toxicokinetic Library

in vivo Toxicokinetic Parameters

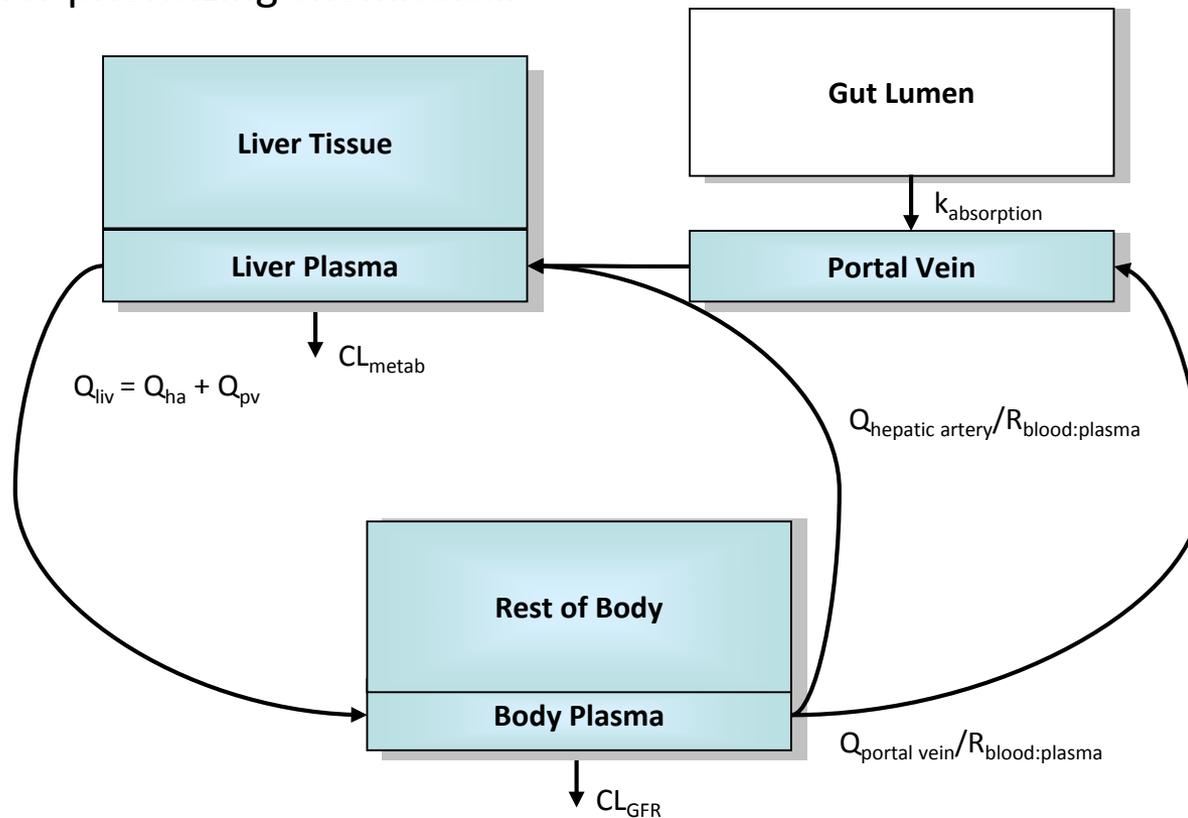


Evaluating Steady-state Conc. (1 mg/kg/day exposure)



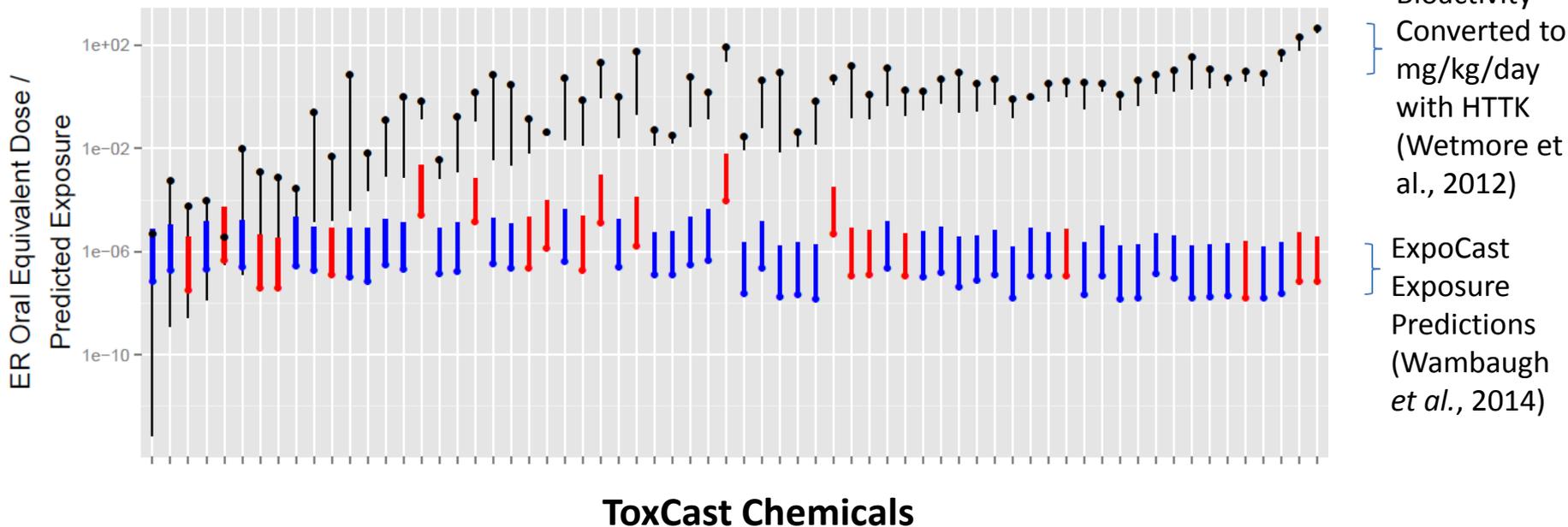
Three Compartment (SimCYP Steady-state) Model

Good enough for prioritizing chemicals...



Pharmacokinetics Allows Context for High Throughput Screening

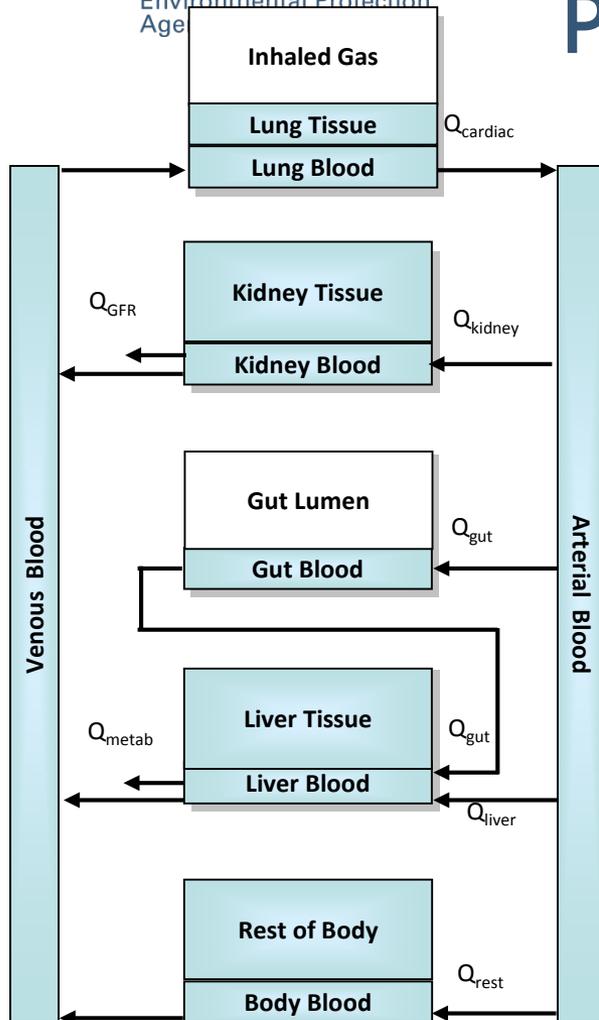
Endocrine disruption AOP (Judson et al., in prep.)



December, 2014 Panel:

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A General Physiologically-based Pharmacokinetic (PBPK) Model



Some tissues (e.g. arterial blood) are simple compartments, while others (e.g. kidney) are compound compartments consisting of separate blood and tissue sections with constant partitioning (i.e., tissue specific partition coefficients)

Exposures are absorbed from reservoirs (gut lumen)

Some specific tissues (lung, kidney, gut, and liver) are modeled explicitly, others (e.g. fat, brain, bones) are lumped into the “Rest of Body” compartment.

Blood flows move the chemical throughout the body. The total blood flow to all tissues equals the cardiac output.

The only ways chemicals “leaves” the body are through metabolism (change into a metabolite) in the liver or excretion by glomerular filtration into the proximal tubules of the kidney (which filter into the lumen of the kidney).

Physiological Data

Tissue	Volume (L/kg)					Blood Flow (ml/min/kg)				
	Mouse	Rat	Dog	Human	Rabbit	Mouse	Rat	Dog	Human	Rabbit
Adipose	0.07	0.07	0.05	0.21	0.05	10.80	1.60	3.50	3.71	12.80
Bone	0.05	0.04	0.04	0.07	0.04	23.31	36.11	1.30	3.36	36.11
Brain	0.02	0.01	0.01	0.02	0.01	13.20	5.20	4.50	10.00	5.20
Gut	0.04	0.03	0.04	0.02	0.05	72.50	39.20	23.00	16.43	44.40
Heart	0.00	0.00	0.01	0.00	0.00	14.00	15.60	5.40	3.43	6.40
Kidneys	0.02	0.01	0.01	0.00	0.01	65.00	36.80	21.60	17.71	32.00
Liver	0.05	0.03	0.03	0.02	0.04	90.00	47.20	30.90	20.71	70.80
Lung	0.01	0.00	0.01	0.01	0.01	2.00	6.22	10.56	2.00	6.22
Muscle	0.37	0.39	0.44	0.38	0.54	45.50	30.00	25.00	10.71	62.00
Skin	0.15	0.17	0.17	0.03	0.04	20.50	23.20	10.00	4.29	23.20
Spleen	0.00	0.00	0.00	0.00	0.00	5.50	4.07	1.65	1.10	3.60
Rest	0.03	0.05	0.00	0.05	0.03	110.19	90.00	5.59	2.97	90.00

Volumes and flows
from Schmitt (2008) +
Nisha Sipes (Rabbit)

Other parameters
from Davies and
Morris (1993) + Nisha
Sipes (Rabbit)

	Units	Mouse	Rat	Dog	Human	Rabbit
Total Body Water	ml/kg	725.00	668.00	603.60	600.00	716
Plasma Volume	ml/kg	50.00	31.20	51.50	42.86	44
Cardiac Output	ml/min/kg	400.00	296.00	120.00	80.00	212
Average BW	kg	0.02	0.25	10.00	70.00	2.5
Total Plasma Protein	g/ml	0.06	0.07	0.09	0.07	0.057
Plasma albumin	g/ml	0.03	0.03	0.03	0.04	0.0387
Plasma a-1-AGP	g/ml	0.01	0.02	0.00	0.00	0.0013
Hematocrit	fraction	0.45	0.46	0.42	0.44	0.36
Urine	ml/min/kg	0.035	0.139	0.021	0.014	0.0417
Bile	ml/min/kg	0.069	0.063	0.008	0.003	0.0833
GFR	ml/min/kg	14.0	5.2	6.1	1.8	3.12

Schmitt (2008) Tissue Composition Data

Tissue	Fraction of total volume ^a		Fraction of cell volume ^b			Fraction of total lipid			pH ^d
	Cells	Interstitialium	Water	Lipid	Protein	Neutral Lipid ^c	Neutral Phospholipid ^c	Acidic Phospholipid ^c	
Adipose	0.86	0.14	0.03	0.92	0.06	1	0.0022	0.0006	7.10
Bone	0.9	0.1	0.26	0.02	0.21	0.85	0.11	0.04	7.00
Brain	1	0.004	0.79	0.11	0.08	0.39	0.48	0.13	7.10
Gut	0.9	0.096	0.78	0.07	0.15	0.69	0.26	0.05	7.00
Heart	0.86	0.14	0.7	0.11	0.19	0.48	0.43	0.09	7.10
Kidneys	0.78	0.22	0.73	0.06	0.21	0.26	0.61	0.13	7.22
Liver	0.82	0.18	0.68	0.08	0.21	0.29	0.59	0.11	7.23
Lung	0.5	0.5	0.74	0.04	0.11	0.51	0.38	0.11	6.60
Muscle	0.88	0.12	0.76	0.01	0.19	0.49	0.42	0.09	6.81
Skin	0.69	0.31	0.47	0.14	0.41	0.9	0.08	0.02	7.00
Spleen	0.79	0.21	0.75	0.02	0.23	0.3	0.54	0.15	7.00
Red blood cells	1–		0.63	0.01	0.33	0.3	0.59	0.1	7.20

a Values taken from (Kawai et al., 1994). Original values given as fraction of total organ volume were rescaled to tissue volume by subtracting vascular volume

b Values taken from (ICRP, 1975). Original values given as fraction of total tissue mass were rescaled to cellular volume as follows: Water fraction of total tissue reduced by interstitial volume and subsequently all values normalized by cellular fraction.

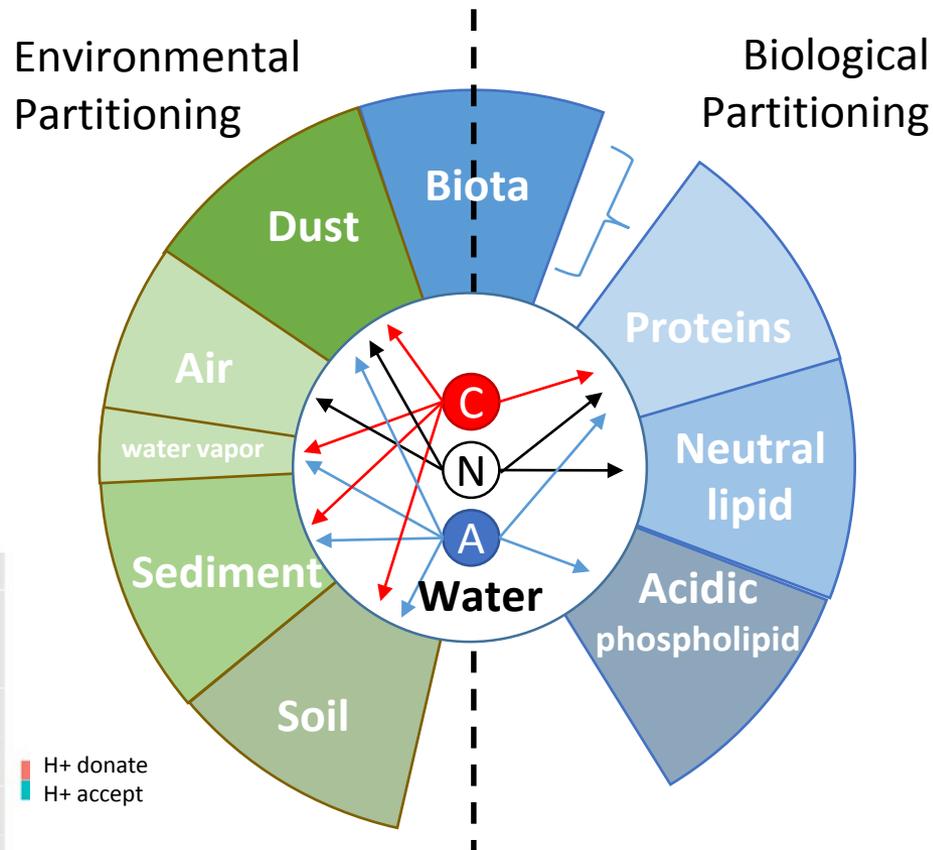
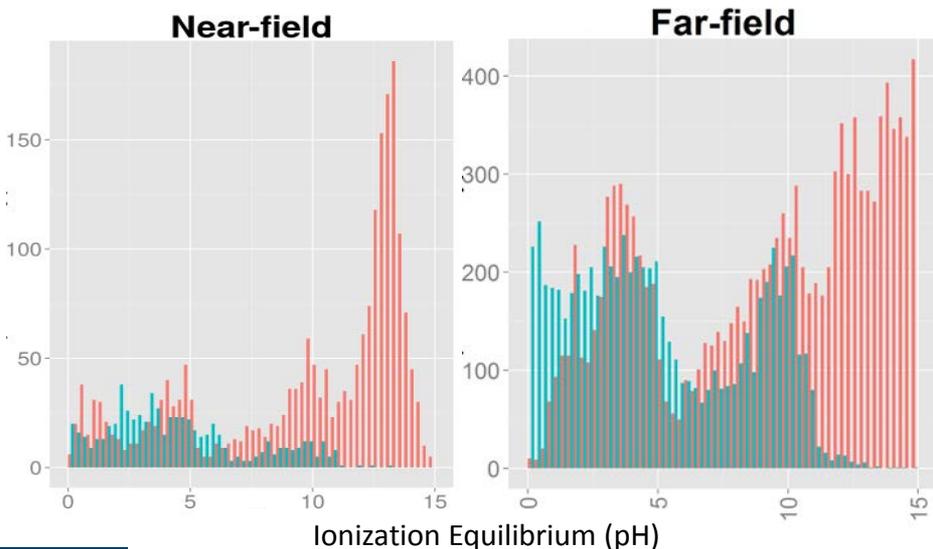
c Data taken from (Rodgers et al., 2005a).

d Values taken from ([Waddell and Bates, 1969], [Malan et al., 1985], [Wood and Schaefer, 1978], [Schanker and Less, 1977], [Harrison and Walker, 1979] and [Civelek et al., 1996]). Mean values were calculated when more than one value was found for the same tissue.

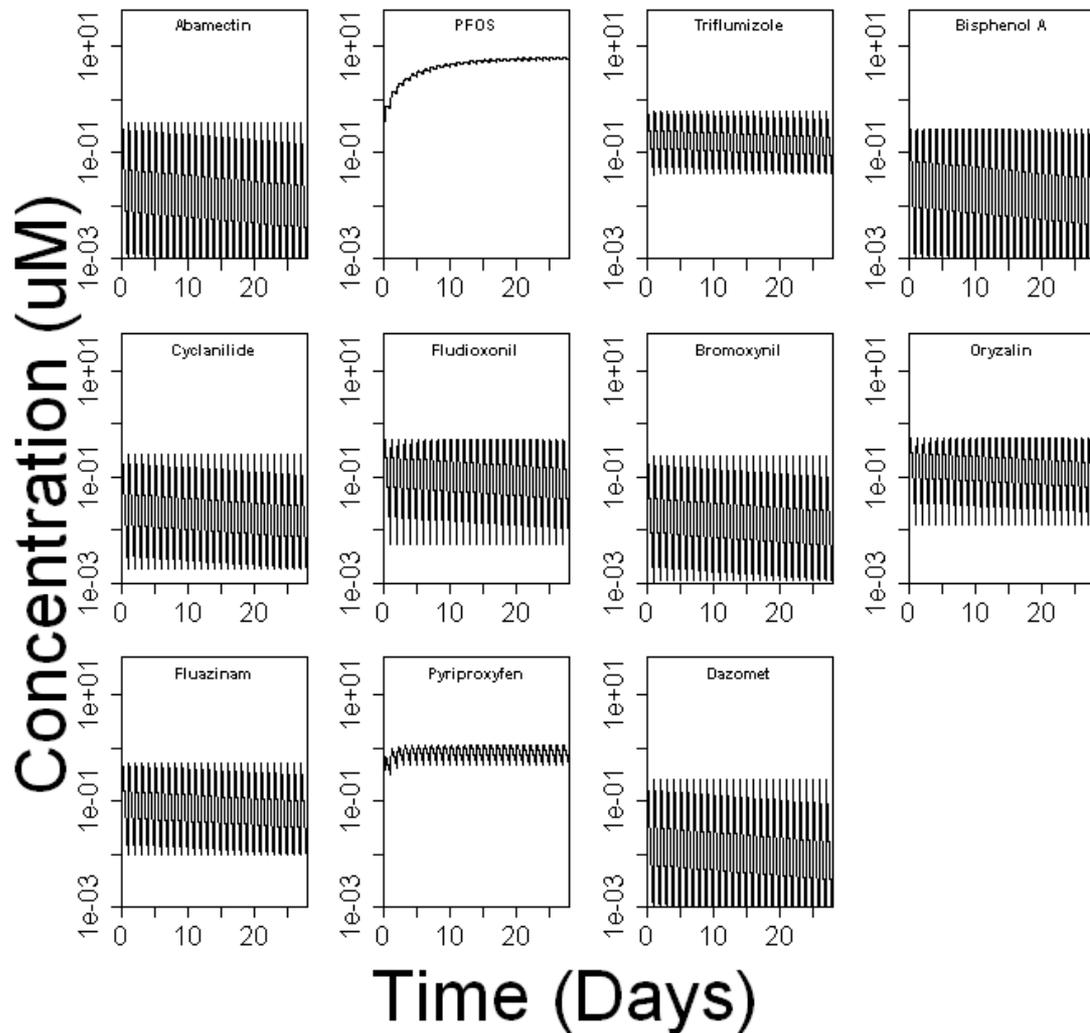
e Data taken from (Gomez et al., 2002).

Prediction of Ionization

- Neutral and ionized species of the same molecule will partition differently into environmental and biological media
- Better models are needed for predicting pKa at different pH for chemicals



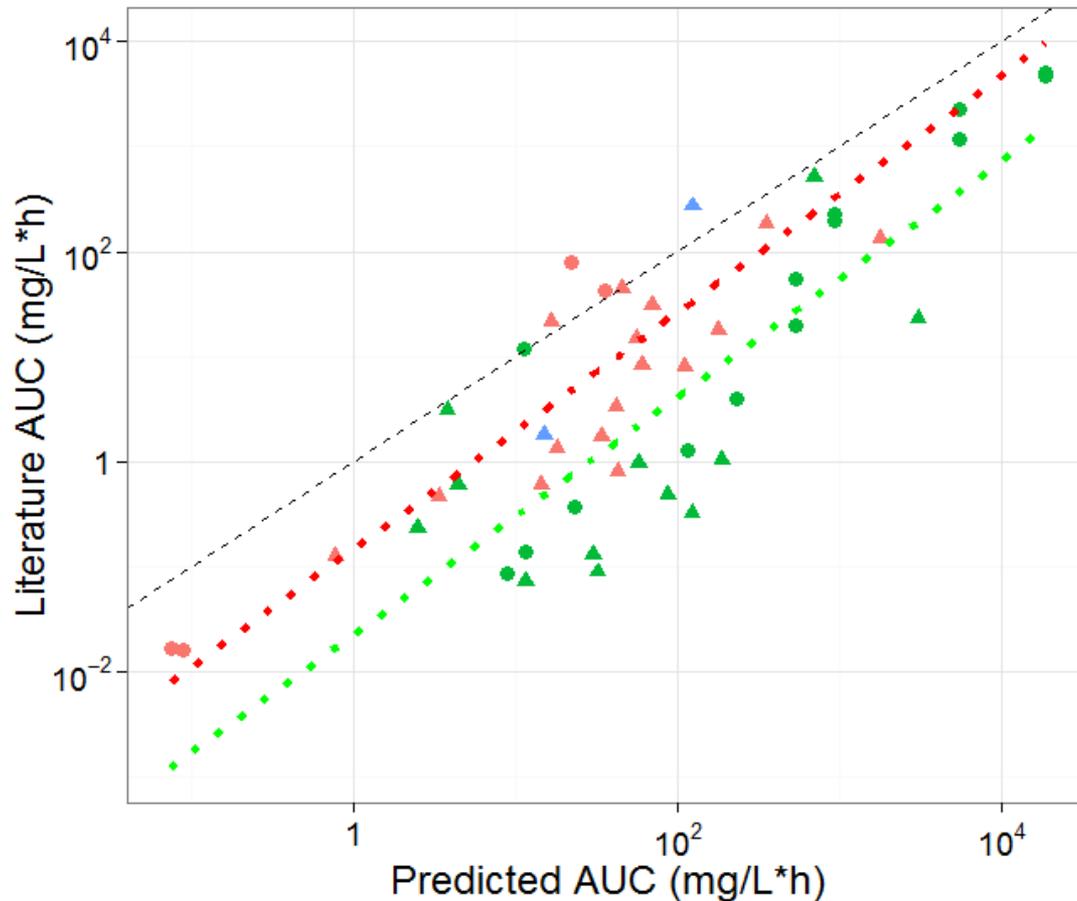
Predicted PK Metrics



Human hepatic concentration of various chemicals as a function of 28 daily doses (10 mg/kg/day)

Can predict mean and peak concentration and time integrated area under the curve (AUC) for various tissues

Evaluating HTPBPK Predictions with *In Vitro* Data



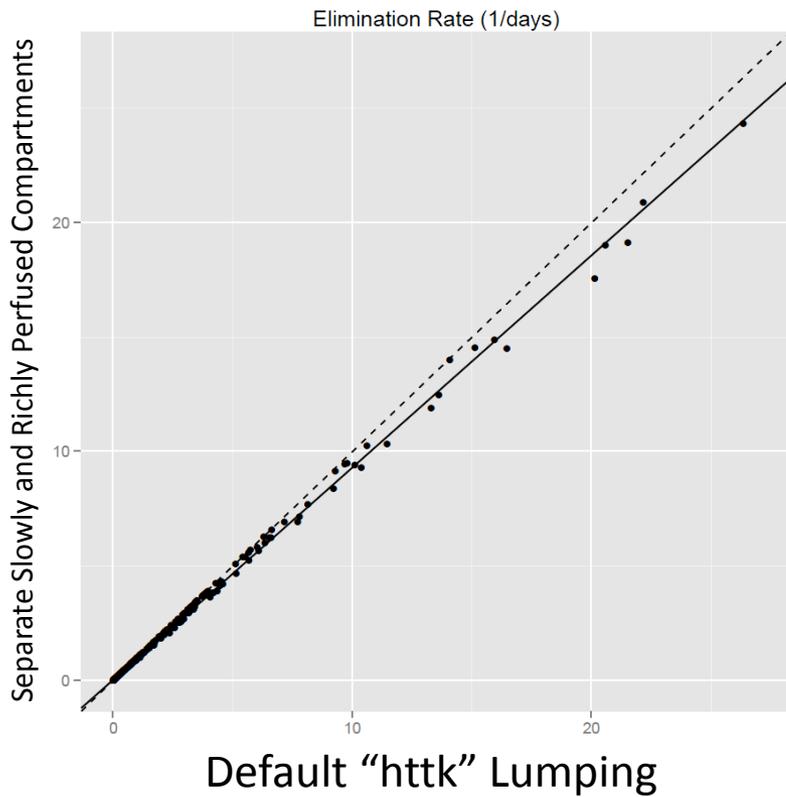
- HTPBPK predictions for the AUC (time integrated plasma concentration or Area Under the Curve)
- *in vivo* measurements from the literature for various treatments (dose and route) of rat.
- Predictions are generally conservative – *i.e.*, predicted AUC higher than measured
- Oral dose AUC ~6.4x higher than intravenous dose AUC

Route ● iv ● po ● sc

Class ● Other (7) ▲ Pharmaceutical (15)

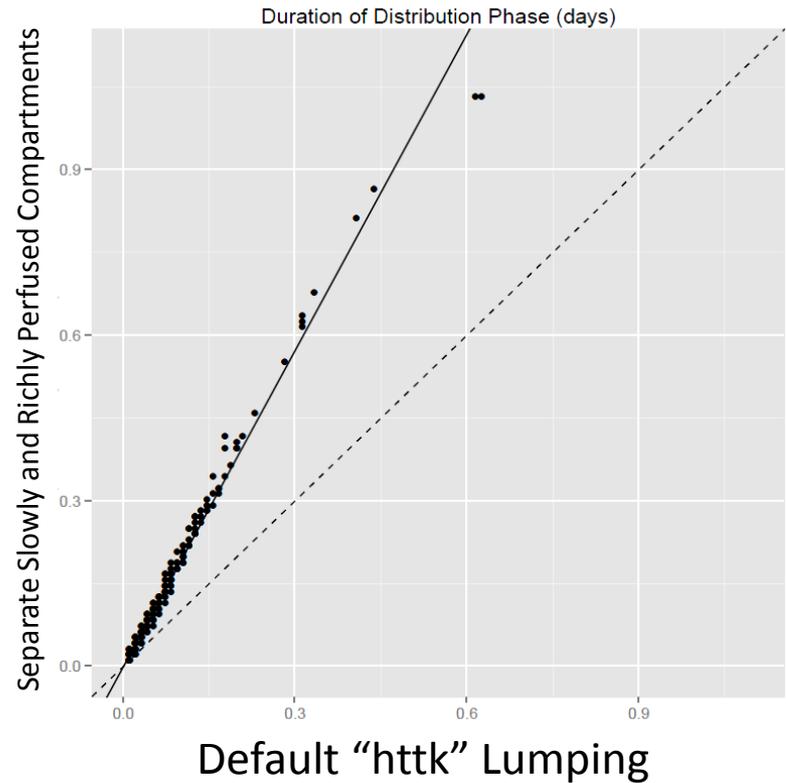
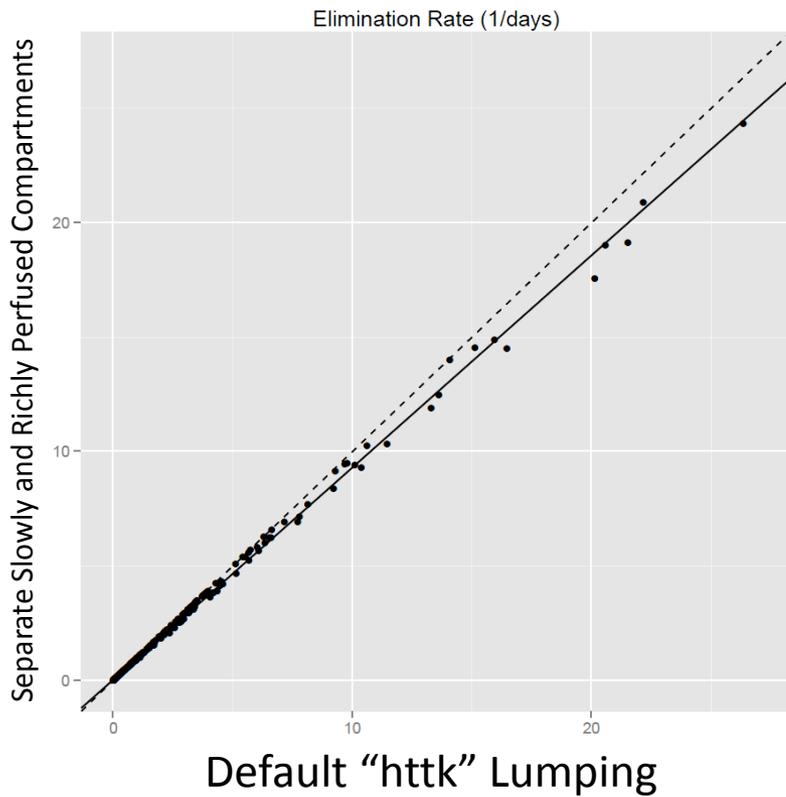
Evaluation Leads to Insight

Examining the impact of lumping – default is liver, kidney, rest of body
What if we separate rest of body into richly and slowly perfused?



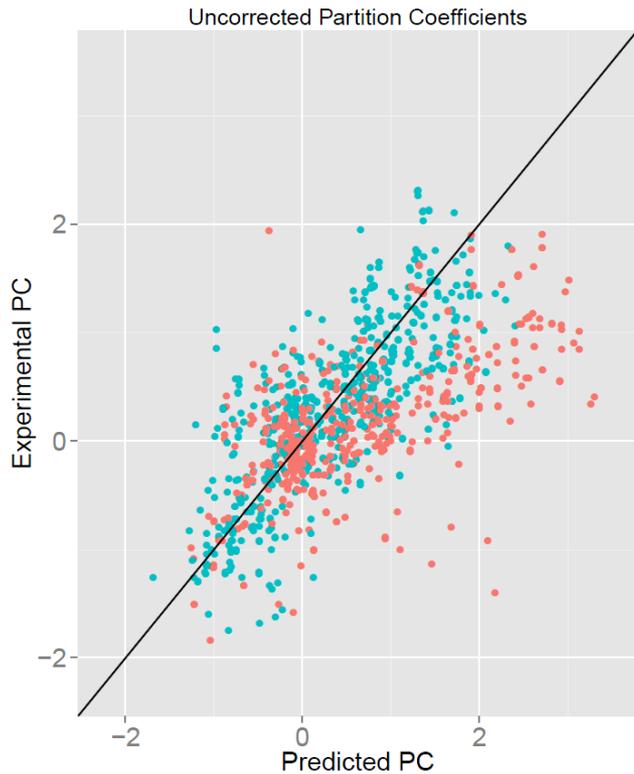
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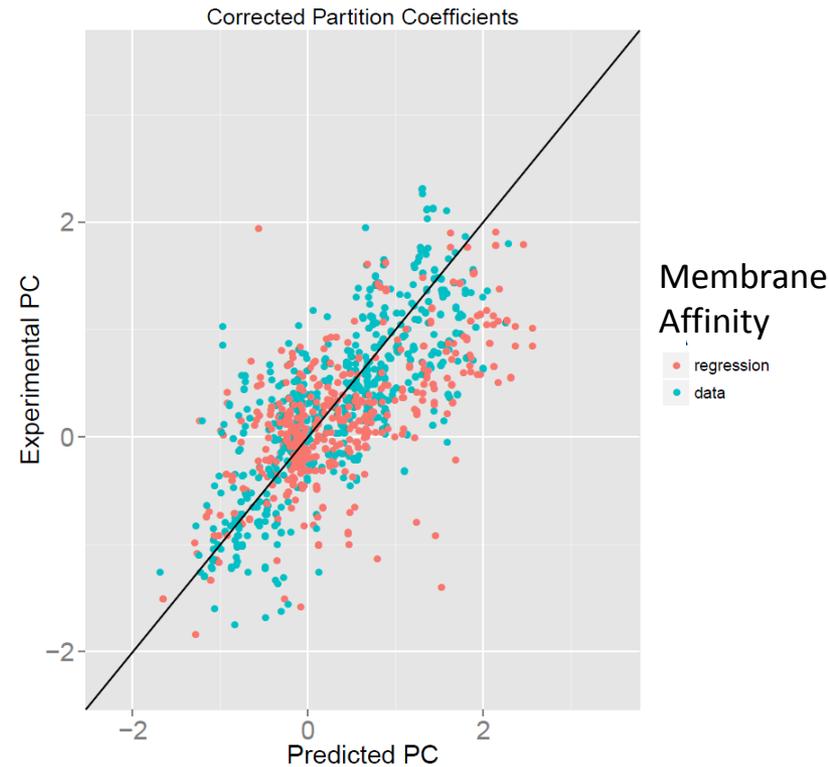


Evaluation Leads to Refined Models

Ongoing refinements of tissue-specific partition coefficient predictions:
Handling high log P, better treatment of ionization (Pearce et al. manuscript)



Membrane
Affinity



Membrane
Affinity

Summary

- Toxicokinetics (TK) provides a bridge between hazard and exposure by predicting tissue concentrations due to exposure
- We must keep in mind the purpose – simple models appear to allow meaningful prioritization of further research
- A primary application of HTTK is “Reverse Dosimetry” or RTK
 - Can infer daily doses that produce plasma concentrations equivalent to the bioactive concentrations,
- We can also use QSAR to build provisional PBTK models

But we must consider parsimony and domain of applicability:

- Do not build beyond the evaluation data
- Carefully determine whether, when, and why model errors are conservative
- Collect PK data from *in vivo* studies to allow larger, systematic studies
- R package “httk” freely available on CRAN allows statistical analyses



Chemical Safety for Sustainability (CSS) Rapid Exposure and Dosimetry (RED) Project

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